Factors Associated with Weight Status, Weight Loss and Attrition

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Abstract

This thesis presents four studies which explore factors associated with weight status, weight loss and attrition. The first and second studies, respectively, examine factors associated with weight loss and attrition. The third study utilises statistical methods to detect and correct for sample selection bias on expected weight loss outcomes and the final study examines risk and time preferences in relation to BMI. Overall we identify several variables exhibiting a significant relationship with weight loss and attrition. Further, we identify and correct for non-random sample selection and, in the final research chapter, find some evidence of a relationship between risk preferences and BMI. Whilst the four research chapters presented can be read independently, each chapter builds upon the findings of the previous studies to present a rich and comprehensive assessment of variables of interest, and throughout the thesis we build an increasingly sophisticated methodological approach to the evaluation of weight status, weight loss and attrition. Our research allows for the identification of potential intervention-generated-inequalities, which are of particular importance for both the continuous development of weight management services and policy. For the first time within the current literature we complement a rich, comprehensive assessment of weight management services with sophisticated quantitative methodological approaches and concepts prevalent in the behavioural economics literature but which have rarely been utilised in studies of obesity. Finally, we evidence a requirement to control for sample selection in economic assessments of weight management services to ensure unbiased estimates within cost-benefit and return-on-investment analyses.

Factors Associated with Weight Status, Weight Loss and Attrition

An exploration of predictors of weight loss and attrition from a weight management service and the effect of time and risk preferences on weight status using data from a field experiment.

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Declaration

Chapter 5 of this thesis has been jointly written with Professor Morten Lau (primary supervisor) using data collected by Harrison, Lau, and Rutström (2010).

Statement of Copyright

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Chapter 1

Introduction

1.1 Introduction

Obesity occurs when energy intake (i.e. food and drink consumption) is greater than energy expenditure (i.e. our metabolism and physical activity) over a prolonged period of time. The prevalence of adult obesity in England has risen from 15% in 1993 to 26% in 2010 (National Obesity Observatory (NOO), 2012) and it is predicted that this will increase to 50% by 2050 (Jebb et al., 2007). The cause of the observed and predicted rise in obesity is complex and includes a multitude of psychological, cultural, behavioural and biological factors (Jebb et al., 2007).

Reducing the prevalence of obesity is of particular importance due to the physical, psychological, social and economic consequences. Obesity leads to an increased risk of a broad range of health conditions including type-2 diabetes, coronary heart disease (CHD) and several types of cancer (NOO, 2013). Psychologically, obesity increases vulnerability to low self-esteem, anxiety and depression (NOO, 2011). Often perceived as socially undesirable, obesity also increases an individual's risk of discrimination (Musingarimi, 2008). The annual cost of overweight and obesity in the UK was estimated at £15.8 billion in 2007 which includes a £4.2 billion annual cost to the National Health Service (NHS) (NOO, 2013).

Obesity has been a recognised public health policy concern since the early 1990s (Musingarimi, 2008). In 2008 the national obesity strategy, "Health Weight, Healthy Lives: A Cross Government Strategy for England" was published (Cross-Government Obesity Unit, 2008). Whilst the strategy outlined activities to reduce obesity at a population level, the key ambition, and single quantifiable goal, of the strategy was to tackle childhood obesity prevalence. This strategic focus on children may in part explain the findings of a progress review published in 2010, two years after the publication of the strategy (Cross-Government Obesity Unit, 2010). It found that whilst progress had been made toward reducing childhood obesity (evidencing a levelling-off of prevalence levels in children under-11), this progress was not reflected in adult obesity prevalence, which continued to rise. In 2010 the UK experienced a change in government and the 2008 strategy was archived. The new Childhood Obesity Plan was published in August 2016 and with publication came a renewed effort to tackle obesity and renewed desire to understand 'what works' in obesity treatment and prevention.

This Chapter aims to provide readers with a synthesised introduction to the vast wider academic literature on obesity starting with the basic questions of:

- What is obesity?
- What causes obesity?
- What are the consequences of obesity?

The chapter continues, outlining that, whilst prevention of obesity is of upmost importance, given the current prevalence, there is an immediate and significant place for effective obesity treatment. Specifically this chapter answer the questions:

- What is effective weight loss?
- How do we achieve this?

Finally, this chapter discusses in more detail the approach and place in the wider system of behavioural weight management programmes for the treatment of obesity; the focus of this thesis. The theoretical and empirical evidence for these programmes is summarised followed by a broader discussion of the strengths and limitations of the approach.

The chapter ends by outlining the research questions tackled by this thesis. The overall schema of the thesis is presented with aims and objectives for each distinct chapter.

1.2: What is Obesity?

From a public health perspective, obesity is defined as "*abnormal or excessive fat accumulation that may impair health*" (Garrow, 1988). Based on this definition, any measurement for the assessment of obesity should, therefore, be able to both provide a measure of body fat and identify a heightened risk of ill-health (Mooney, Baecker and Rundle, 2013).

1.2.1: Measuring Obesity

There are a number of methods by which obesity can be measured. The most common approach is to calculate a Body Mass Index (BMI) score. BMI is calculated by dividing body weight (kilograms) by height (metres) squared. If an adult has a BMI of 30 or over they are classified as obese (see Table 1.1).

BMI range (kg/m^2)	Classification
<18.5	Underweight
18.5-24.9	Healthy Weight
25-29.9	Overweight
30-34.9	Obese I
35-39.9	Obesity II
>40	Obese III

Table 1.1: World Health Organization BMI classification system for adults (WHO, 2000)

A key criticism of the use of BMI as a method of assessing obesity is that is not a direct measure of body fat mass or distribution due to its dependence on measures of height and weight alone (NOO, 2009). It does not adjust, for example, for age or gender which has led many to conclude that it overestimates adiposity in some individuals whilst underestimating it in others (Burkhauser and Cawley, 2008). An example used consistently within the literature is the inability of BMI to distinguish between weight resulting from muscle or fat and, thus, an inability to distinguish between an individual who is physical fit (large muscle mass) and an individual who is obese (large fat mass). Discussions, therefore, tend to focus on the issues of the use of BMI for identification of obesity at an individual level rather than at a population level where many accept that in large numbers individual inaccuracies tend to even out (NOO, 2009).

Despite not being a direct measure of body fat, BMI does largely meet the second criteria of the definition, in that it is rooted in research demonstrating an association with increased risk of mortality and morbidity. The World Health Organisation (WHO) report (WHO, 2000) outlines the associations between BMI and mortality and BMI a number of comorbidities. Specifically it evidences that as BMI increases so does the relative risk of death and diseases, such as, cardiovascular diseases (CVD), high blood pressure, osteoarthritis, some cancers and diabetes (WHO, 2000 and WHO, 2016). A more contentious issue regarding the use of BMI is the seemingly arbitrary bounds of the classifications (outlined in Table 1.1). The expert panel for the WHO report (WHO, 1995) recommended the obesity classifications outlined in Table 1.1 which largely reflected previous recommendations made by Garrow (1981), Bray (1987) and Bray (1978). In the report, the panel acknowledge that "*the method used to establish BMI cut-off points has been largely arbitrary. In essence it has been based upon visual inspection of the relationship between BMI and mortality: the cut-off of 30 is based on the point of flexion of the curve*" (WHO, 1995).

BMI has been used in the selection of the sample examined in Chapters 2, 3 and 4 and for exploring the hypothesised relationship between risk preference, time preference and being overweight in Chapter 5. In the context of research presented in this thesis and reflecting on the discussions outlined in this section, there are a number of points to consider:

1. Whilst the disadvantage of the use of BMI as an indirect measure of adiposity is acknowledged, in the context of the research presented in Chapters 2, 3 and 4 individuals are assessed by a qualified healthcare professional before admittance to the behavioural weight management programme. This referral process ensures only individuals meeting the definition of obesity enter the sample.
2. It is also acknowledged that other measurement methods do exist, however, direct measures of body fat, such as bioelectrical impedance analysis or hydro densitometry, are impractical and often expensive to use at a the scale required by the behavioural weight management programme studied in this thesis. Similarly, other proxy measures of body fat, such as skin fold thickness and waist circumference, are difficult to measure accurately and consistently across large populations (NOO, 2009).
3. Whilst debate continues regarding the bounds of the classifications, those recommended by the WHO reports (WHO, 1995 and WHO 2000) are well-established and, thus, use of BMI in our research provides a firm and consistent basis for evaluation and allows meaningful comparison to existing studies.

To summarise, it is acknowledged that BMI is an imperfect method for assessing obesity and that other methods exist. In the context of our research, however, the benefits of using BMI outweigh the limitations.

1.2.2 Self-Reported vs. Objectively Measured BMI

A further discussion with relevance to our research is the debate regarding the use of self-reported BMI. Research based on objectively measured weight and height, such as that presented in Chapter 2, 3 and 4 is more robust than those utilising self-reported measures, however, there are many other factors that influence the quality of an analysis, this is just one of them.

In a systematic review of the evidence of self-reported measures, Gorber et al. (2007) found that whilst overall the data from the included studies showed an underreporting of weight and an over reporting of height, standard deviations were large indicating a great deal of variability at an individual level (Gorber et al., 2007).

In a further summary review Gosse (2014) find that, of the 25 studies identified, 19 found self-reported BMI to be lower than objectively measured BMI with average misreporting between 0.2-1.5kg/m^2. Further, Gosse (2015) presents an obesity misclassification rate ranging from 4.4% to 11.9% i.e., based on self-reported data, between 4.4% and 11.9% of obese participants were incorrectly classified into the non-obese category. Whilst the review concludes that overall BMI tends to be lower when self-reported, the high variability at an individual level has resulted in no correction method being identified that accurately adjusts for misclassification based on self-reported BMI (Gosse, 2014).

The extent of the issues regarding the use of self-reported BMI is, therefore, dependent on the way in which these measurements are utilised within evaluations. Studies applying BMI as a continuous variable within analyses are at an increased risk of bias compared to those applying BMI as a categorical or binary variable as whilst a continuous variable relies on accurate point estimates, a binary measure of BMI is at a lesser risk of misclassification due to the extent of misreporting. It should be noted, however, that this transformation does not eliminate bias from such approaches.

Within the context of the research presented in Chapter 5, we acknowledge the limitations of using secondary data derived from self-reported BMI but do not attempt to correct for potential misclassification due to the lack of agreed correction method.

1.3 What causes obesity?

1.3.1 Introduction to Complex Systems

As previously outlined, at a basic physiological level, obesity occurs when energy intake (i.e. food and drink consumption) is greater than energy expenditure (i.e. our metabolism and physical activity) over a prolonged period of time.

Framing obesity as a result of energy imbalance is, however, an overly simple conceptual model of obesity. Over the last three decades our understanding and appreciation for the causes of obesity have developed from the simple model presented above (Garrow, 1987) through to more complicated conceptual models of obesity often depicted as nested layers of influence on our behaviours (Davison and Birch, 2001). More recently there has been a growing appreciation for understanding that obesity is the result of a complex system. This is well demonstrated by the Foresight Obesity System Map (Vandenbroeck, 2007) which identifies more than a hundred factors, clustered on multiple layers which are interrelated through more than three hundred connections and one hundred feedback loops (see Figure 1.1). Whist it is impossible to read the individual factors within Figure 1.1, we present the map in its entirety to demonstrate the complexity of the obesity system. For a high definition version of the map please visit:

https://www.gov.uk/government/publications/reducing-obesity-obesity-system-map.

In addition we provide a simplified version of the map outlining the 7 cross-cutting predominant themes (see Figure 1.1(b)).

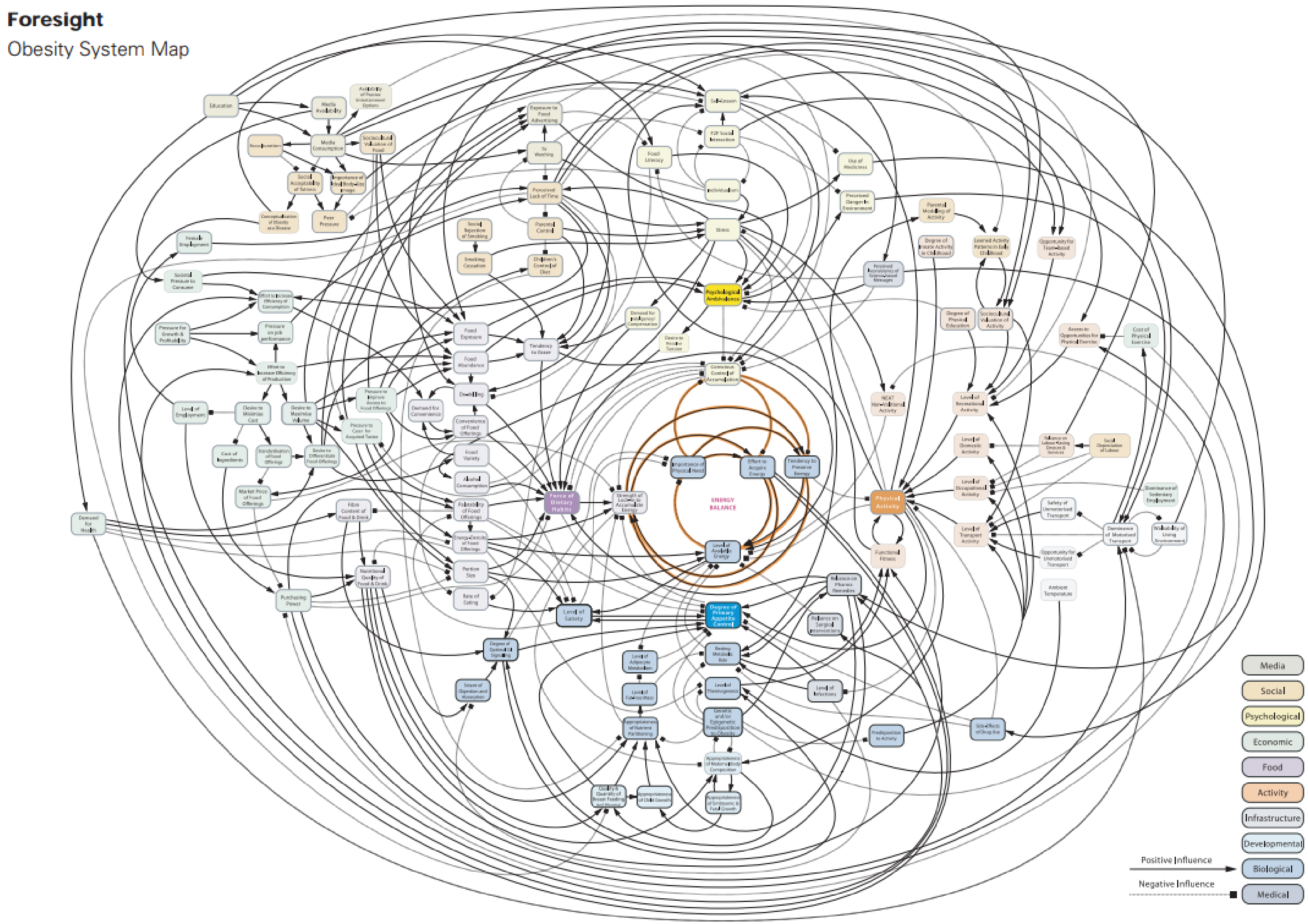

Figure 1.1: Foresight Obesity System Map (Vandenbroeck, 2007)

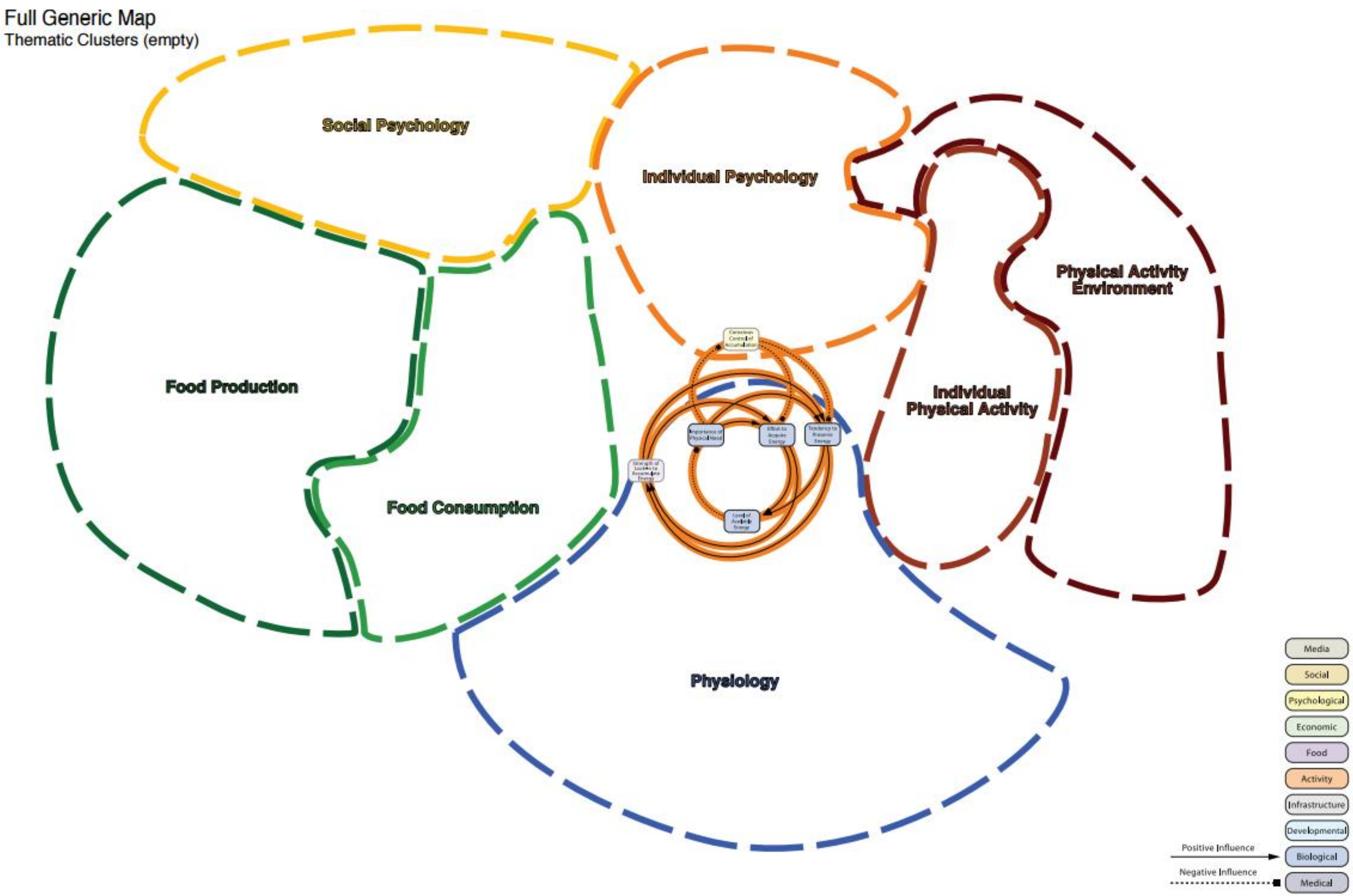

Figure 1.1(b): Foresight Obesity System Map - Thematic Clusters (Vandenbroeck, 2007)

There is no agreed definition of a complex system in the existing literature but Finegood (Finegood, 2011) posits that if a system is *“a set of entities with relationships between them”* then a complex system meets this definition but with *“some added characteristics such as nonlinearity, multiple elements, lack of predictability, interdependence and/or the ability to reduce the system clearly into its distinguishable parts”*. Finegood (2011) also presents and discusses a number of specific features of complex systems which distinguish them from simple and complicated systems and concludes that using either the identified features of a complex system or simply engaging with the Foresight Obesity System map demonstrates an unmistakable recognition of obesity as a complex problem (Finegood, 2011).

Complex conceptual models highlight the need for system wide change but can often overwhelm and even paralyse professionals tasked with tackling obesity. The Foresight Map identifies over a hundred factors which influence obesity, each motivating multiple specific and sometimes conflicting recommendations from various individuals and organisations as to what should be done. In addition, numerous broader recommendations for whole system change resulting from the production of complex conceptual models, such as the Foresight Map, add to the difficultly in deciding what to do.

The focus of the research presented in this thesis is to explore factors associated with weight status, weight loss and attrition in weight management programmes. The contribution of this research to efforts to reduce obesity is the identification of opportunities to increase the effectiveness of weight management attempts by individuals. The following discussion considers our research within the context of complex system thinking. Firstly critiquing the level at which the research is focused (Finegood, 2011) and secondly assessing the focus of the research against a set of principles developed for complex system solutions (Finegood, Karanfil and Matteson, 2010)

Meadows and Wright (2008) argue that the most effective interventions in complex systems are those that can successfully achieve a paradigm shift i.e. those that change the fundamental beliefs that govern the actors in the system. Whilst most impactful, in reality there is not a single intervention which can change the paradigm, it is a culmination of, ideally co-ordinated, actions at various levels throughout the system which result in paradigm shifts. Whilst behavioural weight management programmes, such as that explored in this thesis, will not single-handedly change the system, they have a unique place in the collective effort. Indeed, Hammond (2008) advocates the use of "agent based" or "bottom-up" approaches to tackling complex systems arguing that small changes can be significant to addressing obesity (Hammond, 2008 and Finegood, Karanfil and Matteson, 2010).

To consider what action to take in the context of a complex system, Finegood, Karanfil and Matteson (2010) have developed a framework of principles against which specific actions can be assessed. See Table 1.2. Of particular relevance to the research presented in this thesis are the guiding principles that (1) individuals matter, (2) capacity needs to match complexity, (3) the creation of feedback loops and (4) assess effectiveness.

Solutions to Complex Problems
Consider that individuals matter
Match capacity to complexity
Set functional goals and directions for improvements
Distribute decisions, actions and authority
Form cooperative teams
Create competition
Consider feedback loops and delays
Assess effectiveness

Table 1.2: Solutions to Complex Problems (Finegood et al., 2010 based on Bar-Yam, 2004)

It is not a coincident that the individual is depicted in the centre of the obesity system map (see Figure 1.1). A systems approach highlights that whilst hundreds of factors may be present in a conceptual map, it is the relationship between the individual and these factors that is of upmost importance when developing complex system solutions (Finegood, 2011). Given the huge number of factors contributing to obesity that are identified in the Foresight Map, it is clear that each individual in a population will encounter only a subset of the factors and these subsets will differ from individual to individual. Behaviour change interventions must, therefore, be comprehensive and multidimensional to be effective (Kahn et al., 2009) and to ensure the active ingredients for behaviour change are present requires research such as that presented in this thesis.

The second principle states that interventions must increase the capacity of individuals to match the complexity of the environment they face. Indeed following discussions regarding the complex system science of obesity, Finegood (2011) concludes that *"new approaches including ones that match the capacity of individuals to the challenge posed by their environments…are needed"* (Finegood, 2011). Certainly, the research presented in this thesis adheres to this principle by supporting the continuous improvement of behavioural weight management programmes which equip individuals with the capabilities to counteract factors in the environment which promote overconsumption and sedentary behaviours.

Finally, effective behavioural weight management programmes are in a position in which to create feedback loops to influence other areas of the system. Whilst delivered at an individual level the scale of these interventions is vast. Slimming World (just one provider of weight management services in the UK and the focus of the research presented in Chapters 2, 3 and 4), has over 800,000 individuals attend their groups each week (Slimming World, 2016). As the importance of maintaining a healthy weight infiltrates the beliefs of populations they begin to demand environments which support behaviours in line with these beliefs. Food and drinks producers and retailers, for example, have recognised the consumer trend for products delivering health and wellbeing benefits and are increasing the availability of such foods to consumers (Euromonitor, 2012) and the introduction of the sugar tax was, in part, made possible by public acceptance of the importance of healthy consumption (Campbell, 2015). This in turn loops back to individuals who have increased access to healthy food. Whilst we are not suggesting behavioural weight management programmes are solely responsible for this change in attitudes they certainly play a significant role.

1.3.2 Obesity and Inequalities

Health inequalities refer to the avoidable differences in the health of individuals and groups of individuals (National Institute for Clinical Excellence (NICE), 2012). There is robust evidence for the existence of a 'social gradient' in health whereby individuals in lower socioeconomic statuses disproportionately experience ill health (Marmot et al., 2010). This relationship is reflected in socioeconomic status and obesity risk in adults in the UK (El-Sayed, Scarborough and Galea, 2012).

Over the last 50 years socioeconomic inequalities have increased in the UK leading to widening inequalities in adult obesity, with the rate of obesity rising fastest in lower socioeconomic groups (NOO, 2016). Figure 1.2 presents obesity prevalence for adults (aged 16+ years) in England by household income, education and multiple deprivation quintiles[1].

Figure 1.2 clearly demonstrates a relationship between obesity prevalence and the socioeconomic indictors of income, education and deprivation in women, however, the picture is slightly more complex for men.

[1] Equivalised household income is a measure that takes account of the number of people in the household. For this analysis, households were split into five equal-sized groups banded by income level (income quintiles). Educational attainment is assessed according to individual's highest qualification. The measure of deprivation is based on indices of deprivation scores derived from household postcode.

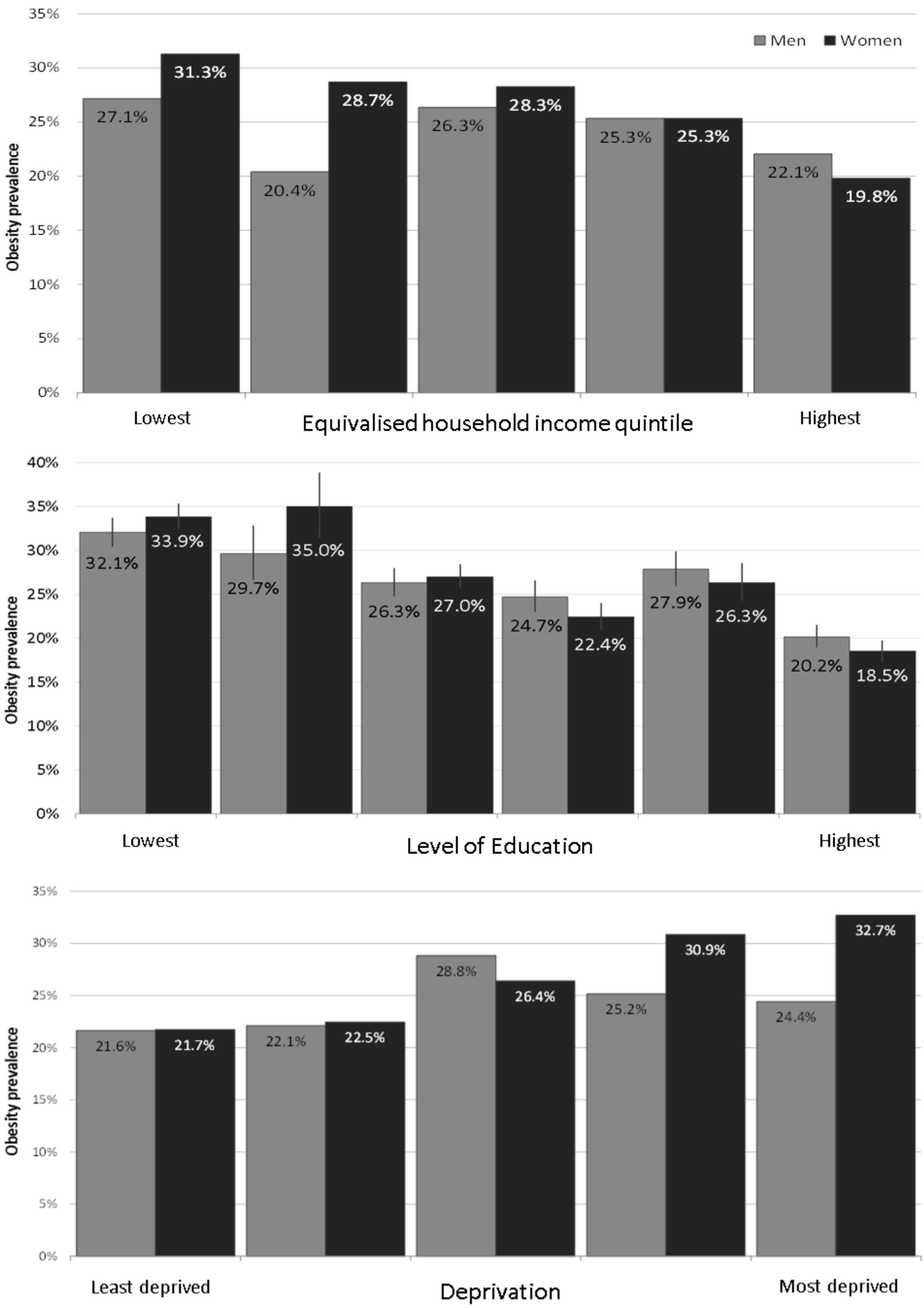

Figure 1.2: The relationship between obesity prevalence and income, education[2] and deprivation quintile in adults in England.

[2] Lowest education level refers to no qualifications. Highest education level refers to degree or equivalent.

Inequalities in obesity are a consequence of an individual's exposure and vulnerability to the multitude of factors identified in the conceptual complex models discussed previously (Friel, Chopra and Satcher, 2007). Every individual is exposed to a varying subset of factors and will respond to these factors differently, thus, creating disparities in individual's probabilities of being obese.

It is argued that individuals of lower socioeconomic status are both exposed to a greater number of factors which increase the likelihood of obesity and are more vulnerable to their detrimental effects. Individuals from lower socioeconomic groups may, for example, be exposed to environments with a higher prevalence of unhealthy food whilst also lacking the capabilities to protect themselves from such environment relative to individuals in higher socioeconomic groups.

Reflecting back to previous discussions, interventions which fundamentally change the exposure to obesogenic environmental, cultural and social factors are often perceived as favourable and most likely to be effective. As previously discussed, these interventions are difficult to implement, requiring coordination from multiple actors within the system and time. In the meantime we have a duty of care to protect those in society who are most vulnerable and as stated before provide capacity to match the complexity of the system.

In the context of the research in this thesis, the importance to ensure that behavioural weight management programmes are not increasing inequalities is taken very seriously. Both County Durham and Darlington, the areas evaluated in this thesis, are in the top 30% most deprived local authorities in England ranking 75th and 95th most deprived out of 326 local authorities respectively (Durham County Council, 2016 and Darlington Borough Council, 2016).

Measures of deprivation are based on 37 indicators grouped into seven distinct domains of income, employment, health and disability, education, skills and training, crime, barriers to housing and living environment. These domains are combined to calculate the Index of Multiple Deprivation (Department for Community and Local Government (DCLG), 2016). The English population is divided geographically into 32,482 Lower Super Output Areas (LOSAs). Each LOSA receives a deprivation score and they are ranked into deprivation deciles where decile 1 indicates the most deprived areas with decile 10 indicating lowest deprivation (DCLG, 2016).

The population of County Durham and Darlington are both skewed towards the more deprived deciles (as outlined in Figures 1.3 and 1.4). When focusing on the Health Domain specifically this skew is much more pronounced (see Figures 1.5 and 1.6). Deprivation scores are assigned at a LSOA population levels.

The behavioural weight management programmes evaluated in this thesis does not condition participation in activity on deprivation. The main criterion is the presence of a BMI ≥30. Due to the relationship between deprivation and obesity we would expect to see a higher proportion of participants from more deprived areas. Whilst our research does not provide this health equity assessment of access, we do provide insights into the important question as to whether factors which influence an individual’s propensity to become obese, such as deprivation, also influence their propensity to lose weight.

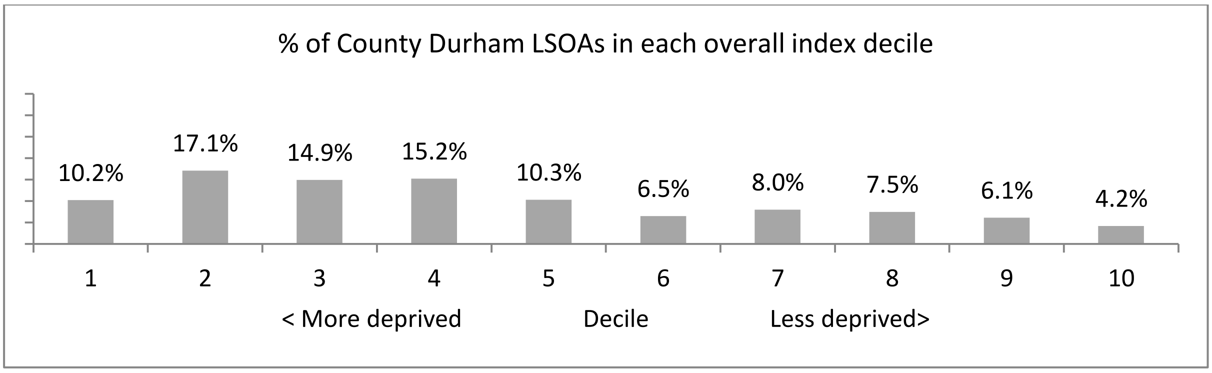

Figure 1.3: - Percentage of LSOAs in County Durham by Deprivation Decile

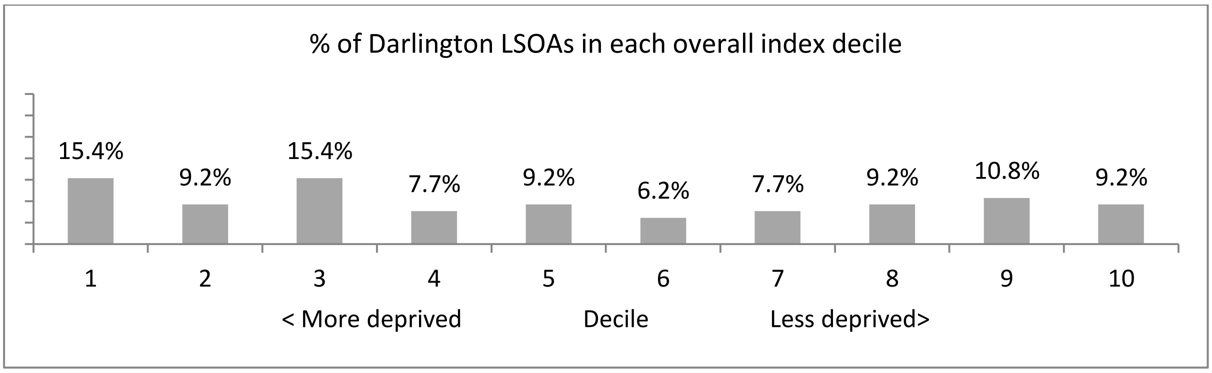

Figure 1.4: - Percentage of LSOAs in Darlington by Deprivation Decile

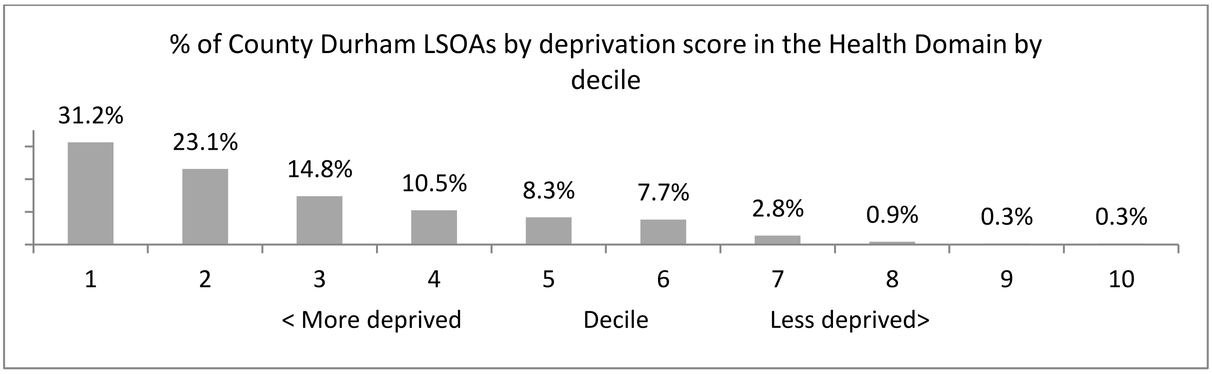

Figure 1.5: Percentage of LSOAs in County Durham by Deprivation Decile (Health Domain)

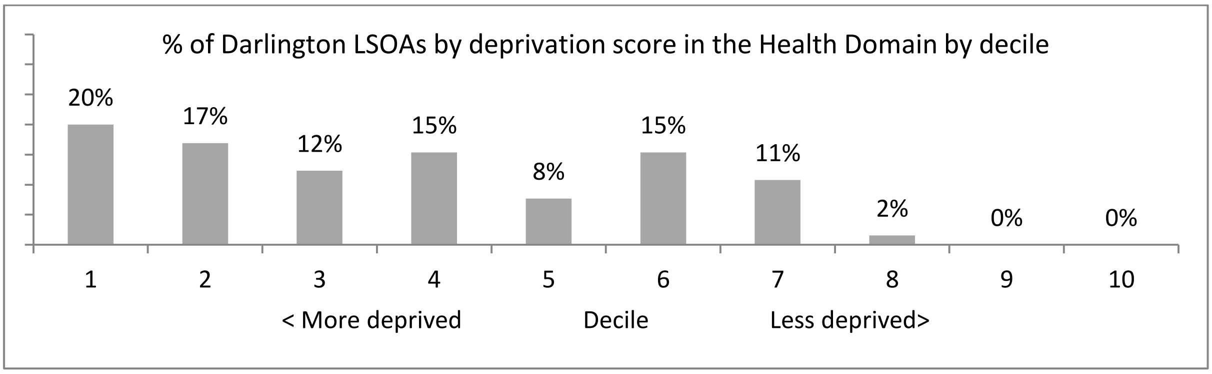

Figure 1.6: Percentage of LSOAs in Darlington by Deprivation Decile (Health Domain)

1.4 What are the consequences?

The previous section outlined the importance of a link between obesity and mortality and morbidity. This section briefly quantifies the consequences of obesity in relation to a variety of health conditions.

The DYNAMO-HIA Project (Dynamic Modelling for Health Impact Assessment) developed an instrument to quantify the health impacts of policies (Lhachimi et al., 2012). Included in the project was a summary of the relative risks of co-morbidities with the categories of obesity. These are presented in Table 1.3. The table provide the relative risk of defined diseases (column 1) according to BMI status and gender (columns 2 to 5). In Table 1.3, relative risk refers to the ratio of the probability of developing disease. The relative risk of diabetes in obese women is 7.0 which suggests obese women are seven times as likely as healthy weight women (defined, in this case, as a BMI of 22) to develop diabetes. Adjustments for age are given as multipliers of the differential risk (i.e. as a multiplier of the difference in relative risk from the base of 1.0). To illustrate, the relative risk of all-cause mortality is 1.20 in overweight men. An age adjustment of x0.95 (individuals over 60, see column 6) leads to a relative risk of 1.19.[3] Whilst this information is not utilised within this thesis, it is an important demonstration of the relationship between obesity and clinical outcomes.

[3] Adjusted relative risk = 1 + the adjustment multiplier x (relative risk – 1)

Disease	Relative Risk Overweight		Relative Risk Obesity		Age adjustments
	Men	Women	Men	Women	(multiplier of differential risk)
All-cause mortality	1.20	1.15	1.55	1.50	x 0.98 from age 50 x 0.95 from age 60 x 0.90 from age 70
Ischaemic Heart Disease	1.35	1.35	2.00	2.00	x 0.70 age over 65
Stroke	1.20	1.20	1.50	1.50	x 0.75 from age 65
Diabetes	2.25	2.30	5.50	7.00	x 0.92 from age 60
COPD	1.00	1.00	1.00	1.00	-
Cancer- Lung	0.80	0.88	0.65	0.70	-
Cancer- Breast	1.00	1.00*	1.00	1.00**	[*Overweight women: 1.12 over age 50 **Obese women: 1.25 over age 50]
Cancer-Oral	0.80	0.88	0.65	0.70	-
Cancer- Colorectal	1.20	1.08	1.40	1.10	x 0.90 from age 45
Cancer- Oesophageal (all)	1.00	1.00	1.00	1.00	-
Cancer- Kidney	1.24	1.32	1.55	1.80	-
Cancer- gallbladder	1.05	1.35	1.25	1.85	Men: x 1.17 from age 45 Women: x 0.80 from age 45
Cancer- Womb	-	1.50	-	2.50	-

Table 1.3: Estimated relative risk of disease by BMI category- overweight and obese (Lhachimi et al., 2012).

1.5 What would make a difference?

Of equal if not greater importance, given the current prevalence of obesity, is an understanding of weight loss and risk.

In the 1970s an important distinction was made between statistically significant and clinically significant weight change (Williamson, Bray and Ryan, 2015). The first simply evidences that any difference in weight (whether between a control and treatment group or observed in an individual pre and post engagement in a weight management service) is caused by something other than random chance. Clinically significance refers to a change in weight which results in a meaningful reduction in the risk of ill-health. The distinction is particularly pertinent for commissioners of services who need to understand what weight loss is worthwhile. The question, therefore, is what defines clinically significant weight loss (Williamson, Bray and Ryan, 2015)?

The initial suggestion was simply to utilise the agreed BMI threshold for obesity (>30) and, thus, define clinically significant weight loss as a reduction that brings an individual under the threshold. Several researchers, however, presented arguments to define clinically significant weight loss in terms of percentage weight loss (Williamson, Bray and Ryan, 2015), making recommendation from 5% to 10% reduction in body weight (Rossner, 1991; Goldstein, 1992 and Blackburn, 1995). Following an evidence based review of the literature Jensen et al. (2014) concluded that meaningful clinical outcomes were seen at 3% weight loss (for glycaemic measures and triglycerides) and 5% weight loss (for blood pressure and HDL and LDL cholesterol) (Jensen et al., 2014). The threshold of 5% weight loss was, therefore, largely adopted as a robust marker of intervention success (Williamson, Bray and Ryan, 2015).

The research presented in this thesis uses 5% weight loss as a binary measure of a clinically significant outcome. A key question is, therefore, is this reasonable? There are three important discussions when considering this question:

1. Does achieving 5% weight loss evidence an increased capacity of an individual to reduce their weight and form beneficial consumption and/or physical activity habits?
2. With the growing evidence of the positive effects of greater weight loss in the early stages of weight loss attempts, should the recommended threshold be increased?
3. On the other hand, lesser weight loss (e.g. 3%) has clinically significant benefits. Should this be discounted?

Considering the first question, the Foresight Map presented earlier, is designed to be a "*comprehensive 'whole systems' view of the determinants of energy balance that exists*" (Vandenbroeck, 2007). Further, as previously stated, obesity can be viewed as a consequence of an individual's exposure and vulnerability to the multitude of factors identified. Although perhaps an overly simplistic depiction, the achievement of clinically significant weight loss can be reduced down to either a change in a factor(s) external to the individual or a change in a factor(s) internal to the individual which results in a change in the relationship an individual has with the factor(s) in the system which previously hindered the achievement of clinically significant weight loss or, were indeed, promoting weight gain. Behavioural weight management programmes are largely based on providing individuals with the skills they require to successfully lose weight. In studies where a control group exists i.e. factors external to the individual are controlled for, significant weight loss does suggest a change in factors internal to the individual. Assuming we do not change the biology of an individual, this provides a theoretical basis for the 5% weight loss outcome as evidence of an increased capacity of individuals and, thus, a satisfactory criterion to define clinically significant weight loss.

Conversely, a key deliverable of a weight management programme is that learned consumption and energy expending behaviours should become 'habits' i.e. that the behaviours are no longer conscious activities but are automatic and sustained (Lally, Chipperfield and Wardle, 2008). In this case the achievement of 5% weight loss does little to evidence this. Key to the definition of habitual behaviour is the concept of a pattern of behaviour over time which a binary measure of weight loss comparing two points in time does not represent.

Considering the second of the three questions, greater initial weight loss is a strong predictor of longer-term weight loss. Much discussion regarding the theoretical underpinning of this observation is provided in the following chapters. In the context of the current discussion, a typical twelve week behavioural weight management programme may achieve a 5% weight loss in individuals but this may not represent the achievement of a healthy BMI (i.e. ≤25). As previously discussed, increased individual capacity including the development of healthy habitual behaviours are thought to enable continued weight loss beyond the timescales of the intervention. If greater initial weight loss results in an increased probability of continued weight loss, it, therefore, can be argued that outcome measures of interventions should be increased to reflect this evidence. Whilst some may argue that a greater outcome measure is based on behavioural recommendations rather than clinical significance, reductions in relative risks of ill health are only maintained if weight reduction is maintained, therefore, an increased outcome measure reflects both behavioural and clinical requirements. There is, however, a critical issue with simply increasing the outcome measurement to achieve higher initial weight loss and that is that it does not include a temporal element. Of interest to this discussion is the growing evidence regarding the use of Very Low Energy Diets (VLED), which consist of an initial period of highly restricted consumption resulting in high initial weight loss, followed by a period of more conservative weight loss and finally weight maintenance. One reason for the increased interest in this approach is the robust evidence regarding the effect of greater initial weight loss on longer term outcomes. In the context of this discussion, whilst, there is no agreed definition of early/initial weight loss, simply comparing two points in time does not reflect a pattern of weight loss which is of interest in, for example, VLED approaches.

A further argument against increasing the outcome measurement and, in fact, an argument for the recommended percentage weight loss to be decreased, is contained in the original findings of Jensen et al. (2014) which concluded that even lower weight loss (>3%) may bring clinically significant benefits in some risk factors and for some patients (Williamson, Bray and Ryan, 2015). The problem with setting an outcome measure of 5% or greater is that it reduces the probability of the implementation of interventions that, whilst not meeting this criterion, could result in clinically significant outcomes. Disregarding interventions that achieve a lower outcome may be detrimental particularly if these interventions are low cost and can be implemented on a large scale.

To summarise the discussions, the 5% outcome measure is a clinically meaningful measure of weight loss. Whilst discussions exist as to whether it should be increased or decreased there is no conclusive robust evidence to introduce such a change. As a well-established measurement, it provides a benchmark by which to compare interventions and, thus, is correctly utilised within the research of the thesis. As is presented in further chapters, it is complimented by the inclusion of other measures of success, thus, not disregarding the discussions of this section.

1.6 What intervention options exist?

Throughout the previous sections discussions have referred back to behavioural weight management programmes due to the focus of the research presented in this thesis. Alluded to in the discussion of a complex systems approach, it is important to acknowledge the range of policy options that exist and where our research fits in.

The first discussion frames the various options for intervention in terms of the stage of prevention it targets. The prevention of obesity is most often referred to as (1) primary, (2) secondary or (3) tertiary. Primary prevention refers to interventions designed to prevent the development of obesity. Secondary prevention refers to interventions designed to reduce the number of existing cases of obesity. Tertiary prevention refers to interventions designed to stabilise or reduce the amount of disability associated with the obesity (Nammi et al., 2004). In addition to the three stages framework is the concept of "primordial prevention", a term first coined by Strasser in 1978 (Strasser, 1978). Primordial prevention refers to "*interventions which aim to avoid the emergence of the social, economic and cultural patterns of living that are known to contribute to an elevated risk of disease*" (Strasser, 1978), thus, the stages of obesity prevention can be depicted as outlined in Figure 1.7.

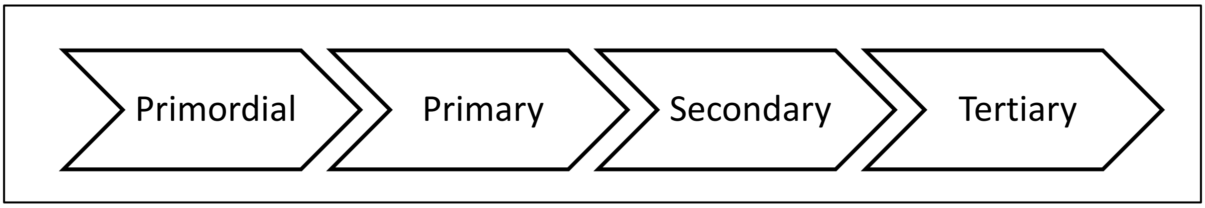

Figure 1.7: Levels of Obesity Prevention

Reflecting back to previous discussions of complex systems, it is clear that many of the identified factors exist beyond the capacity of the individual, communities and even the health sector to change and, thus, to achieve a paradigm shift there is a requirement for a multi-sector approach to primordial obesity prevention. This thesis cannot outline all specific interventions available to tackle obesity at this stage of prevention, however, some examples of primordial prevention interventions include; (1) taxes on unhealthy food and beverages, (2) the restriction of marketing of unhealthy food to children and (3) planning of the urban environment to encourage physical activity (Public Health England (PHE), 2015). Few can argue against the importance of primordial and primary prevention interventions, however, they are often politically sensitive, expensive, can take a long time to implement and often exhibit a substantial lag between implementation and changes in health outcomes. Whilst investment must be made in primordial and primary interventions we face a society in which the majority of individuals are overweight and obese and, thus, an urgent requirement for effective secondary and tertiary prevention as well, in other words, a whole-systems approach to obesity.

PHE and The Association of Public Health Directors (APHD) have recently commissioned a piece of work to design a whole systems approach to preventing and tackling obesity (Leeds Beckett University, 2016). This is a major piece of work which signifies governmental acknowledgement of obesity as a consequence of a complex system. It is entirely appropriate for government to build this broader picture of what works as they are in a position to affect whole-systems change and contribute significantly to the paradigm shift outlined previously. To understand where our research fits into this approach is it useful to consider Mahli et al.'s (2009) framework of intervention levels for obesity. See Figure 1.8.

Intervention Level	Examples of Action Statements at That Level
Paradigm	• Reframe obesity as a consequence of environmental inequities and not just the result of poor personal choices. • Develop a systems approach that recognizes the role that social conditions, politics, and economic forces play in prevention and treatment.
Goals	• Establish targets to achieve healthy weights for children through physical activity and healthy food choices. • Build trust across the multiple sectors that need to work to together to address obesity and chronic disease prevention. • Reduce inequities in the determinants of health that lead to inequities in health status. • Create a social expectation to emphasize prevention as more important than minimally extending life through expensive procedures.
System Structure	• Identify a lead department or agency for federal interdepartmental action on healthy weights for children. • Enable coalitions of health, environmental, labor, poverty, and public policy advocates to work together on common beneficial prevention projects. • Harmonize primary, secondary, and tertiary prevention program messages and policies across jurisdictions. • Implement the appropriate mix of individually-focused and environmentally-focused effort.
Feedback and Delays	• Assess effectiveness of self-regulation of marketing to children. • Establish legislative or regulatory action to enforce workplace standards for mothers who choose to breastfeed. • Conduct more research on natural policy and program experiments.
Structural Elements	• Establish a comprehensive public awareness campaign on healthy weights for children. • Implement a mandatory, standardized, simple, front of package

Figure 1.8: Sample Actions According to the Intervention Level Framework for Obesity and Chronic Disease (Finegood, 2011 and Mahli, 2009)

The whole systems approach commissioned by PHE and APHD represents an intervention at the system structure and goals levels of the framework as the objective of the programme is to translate the framework set out by Foresight into a 'Whole Systems Approach' which links together the factors that influence obesity and recommends co-ordinated action and integration across multiple sectors including health, social care, planning, housing, transport and business (Leeds Beckett University, 2016). To achieve this, however, requires evidence from the lower levels including the feedback and delays and structural intervention levels where our research is located. It is evidence, such as that presented in this thesis, which provides important pieces of the whole systems puzzle.

A further useful method by which to consider policy intervention is the Nuffield Council on Bioethics Ladder of Intervention (Nuffield Council on Bioethics, 2007). See Figure 1.9.

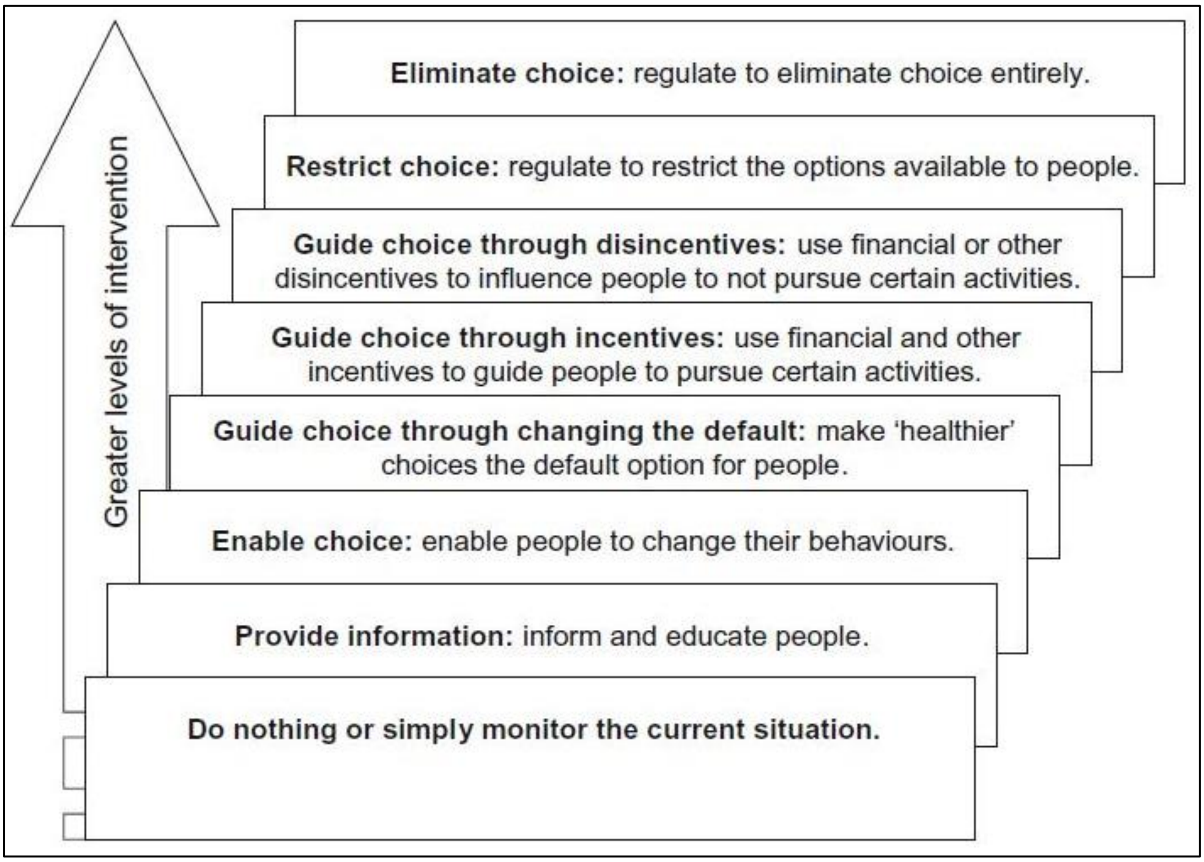

Figure 1.9: Nuffield Council on Bioethics Ladder of Intervention (Nuffield Council on Bioethics, 2007).

The Ladder of Intervention outlines the range of options available to government and policy makers from individual freedom and responsibility at the bottom of the ladder to state intervention at the top. Table 1.4 outlines examples of obesity interventions for each rung of the ladder.

Rung	Intervention
Eliminate choice	Prohibition of sugar sweetened beverages.
Restrict choice	Outlawing sugar sweetened beverage from schools.
Disincentives	Introduction and enforcement of a sugar levy.
Incentives	Provision of vouchers for healthy food items to parents.
Changing the default	Automatic enrolment to weight management support.
Enable choice	Behavioural weight management interventions.
Provide Information	Social marketing campaigns.
Do nothing	-

Table 1.4: Examples of obesity interventions for each rung of the Nuffield Council on Bioethics Ladder of Intervention.

Appropriate choice of policy in the case of obesity is likely to be driven by a balance between the economic costs, health benefits and societal benefits against the erosion of individual freedom from policies higher up the ladder. Further, choice of policy will also depend on the extent to which individuals make rational decisions. These discussions are picked up later in this chapter. In the context of complex systems thinking what is likely to be required is coordinated interventions across the spectrum of policy options. Successful use of policy options from most rungs of the ladder have been implemented in the area of smoking cessation, where, one can observe the beginnings of a paradigm shift. Public information campaigns, widespread smoking cessation services, the ban on smoking in public places and increased taxation on tobacco has over time resulted in a significant reduction in smoking prevalence (Finegood, 2011). Reflective of the previous discussion, weight management services will not eradicate obesity; however, they have a clear and significant contribution to a broader policy approach.

Before moving onto the next section which discusses behavioural weight management programmes in more detail, it is worth summarising discussion, thus far.

- The foundations for obesity research have been outlined through discussions of the definition and appropriate measurement of obesity and weight loss.
- The causes of obesity have been discussed in the context of complex system thinking and it has been acknowledged that individual behaviour alone is not responsible.
- Solutions for obesity have been presented in the context of three frameworks (see Figures 1.7, 1.8 and 1.9) all promoting a whole-systems approach to obesity.
- Throughout all discussion the contribution of behavioural weight management programmes to the whole systems approach has been outlined, evidencing the requirement for treatment of obesity and the importance of focusing on the individual and building capacity to match the complexity they face.

1.7 What are behavioural weight management programmes?

Behavioural weight management programmes, also referred to as Tier 2 weight management interventions, refer to behaviour change programmes with the objective to reduce energy intake through diet modification and/or increase energy expenditure through physical activity. They are non-surgical, non-pharmacological approaches to weight loss. A graphical representation of the tiers of obesity treatment can be found in Appendix 3.

1.7.1 What are the objectives of behavioural weight management programmes?

There is no standard specification for behavioural weight management programmes; however, NICE have published guidance which includes recommended outcomes measures (NICE, 2014). Weight related outcomes include:

- Average weight loss among participants is 3%.
- At least 30% of participants losing at least 5%of their initial body weight.
- Are effective at 12 months or beyond.

(NICE, 2014)

The guidance is directly reflective of the evidence base for weight loss outcomes presented previously recommending both 5% and 3% weight loss outcomes. Further, and of importance is the recommended longer-term outcome. The guidance does not specify a target longer term weight loss outcome but does recommend that post intervention, at least no weight gain should be observed. Discussion regarding all outcomes will be revisited later in this section.

Local commissioners of these services are at liberty to tailor and supplement these objectives to suit local need. Due to the strong relationship between obesity and deprivation (see previous discussion), a common addition to the above objectives is the requirement for a specified proportion of participants to reside in areas of high deprivation.

1.7.2 How do they achieve these objectives?

As there is no standard specification, the delivery of programmes can differ by locality. NICE Guidance (NICE, 2014) provides broad recommendations for the content of programmes. In summary a programme should:

- Be multicomponent i.e. address diet, physical activity and behaviour change.
- Focus on lifetime change and the prevention of weight regain.
- Last for a minimum of three months with weekly or fortnightly sessions.
- Set achievable weight loss goals for each stage of the programme.
- Provide tailored dietary and physical activity goals for individuals.
- Use a variety of behaviour change methods.
- Tailor programmes to the needs of the target population.
- Monitor weight and indicators of behaviour change throughout the programme.
- Adopt a respectful, non-judgemental approach.

(NICE, 2014)

Designed to be large scale interventions, behavioural weight management programmes are most often delivered as group sessions due to the relative cost effectiveness. Although outlined in NICE guidance for economic reasons, there is growing evidence that the use of group based approaches are also more effective than individual based interventions when evaluating weight loss (Paul-Ebhohimhen and Avenell, 2009). The specification for the behavioural weight management programme studied in this thesis adheres to the recommendations outlined above. See Appendix 7.

Whilst NICE guidance (NICE, 2014) is an important resource for the commissioning of behavioural weight management programmes it clearly states that; "*the guidance does not override the responsibility of healthcare professionals to make decisions appropriate to the circumstances of the individual patient*" (NICE, 2014). The inclusion of this statement is, in some sense, an acknowledgement of the complexity of obesity and requirement to reflect this complexity in clinical and commissioning decision making. In fact, the guidance outlines a number of gaps in the evidence base for behavioural weight management programmes which if filled would support commissioners and clinicians to increase the effectiveness of approaches. Of particular relevance to the research presented in this thesis is the identified "*lack of evidence on the effect of sexual orientation, disability, religion, place of residence, occupation, education, socioeconomic position or social capital on the effectiveness of lifestyle weight management programme [and]…a lack of analysis of participants by age and gender*" (NICE, 2014).

The research presented in this thesis intends to contribute evidence required to fill this gap in knowledge. The intended purpose of the sub-group analyses in Chapter 2, 3 ,4 and 5 is the identification of groups of individuals that may require additional or tailored support to achieve significant weight loss outcomes, which in turn should help ensure that such approaches to the treatment of obesity do not widen inequalities.

1.7.3 What are the behavioural change theories that underpin these programmes?

In the broad context of preventative health, there are many examples of effective behaviour change interventions, however; there are equally many examples of ineffective interventions (Davis et al., 2015). It is argued that to maximise effectiveness, behaviour change interventions should be built on a solid theoretical understanding of both mediators and moderators of behaviour (Davis et al., 2015). This section provides discussions regarding the theoretical underpinnings of weight management. We begin by discussing the traditional use of theoretical frameworks, followed by discussions of alternative approaches and their limitations, wrapping up discussion with the opportunity for the integration of behavioural economic principles into theoretical approaches to weight management.

What theoretical frameworks are applied in behaviour change interventions?

In the context of current discussions, theoretical frameworks refer to integrative models of behavioural change theory which attempt to explain behaviour. Traditionally, these frameworks, which attempt to encapsulate all factors which effect behaviour, have been the basis for developing interventions to promote health-related behaviour change. Numerous theoretical frameworks are available to individuals who are developing interventions; in fact, a recent scoping review identified eighty-two frameworks designed to support the development of interventions to change health-related behaviours (Davis et al., 2015). Despite the numerous options available, three frameworks were reported to be used most prominently within weight management intervention design. These are presented on the following page.

– Theory of Planned Behaviour also known as the Theory of Reasoned Action (Ajzen, 1985)

– Transtheorectical Model also known as the Stage of Change Model (Prochaska and Veliser, 1997)

– Social Cognitive Theory (Bandura, 1986)

(Davis et al., 2015)

As an illustrative example of a prominently utilised theoretical framework; the theory of planned behaviour posits that observed behaviour results from behavioural intentions which are shaped by three constructs; (1) attitude toward behaviour, (2) subjective norms, and (3) perceived behavioural control (Ajzen, 1985). See Figure 1.10.

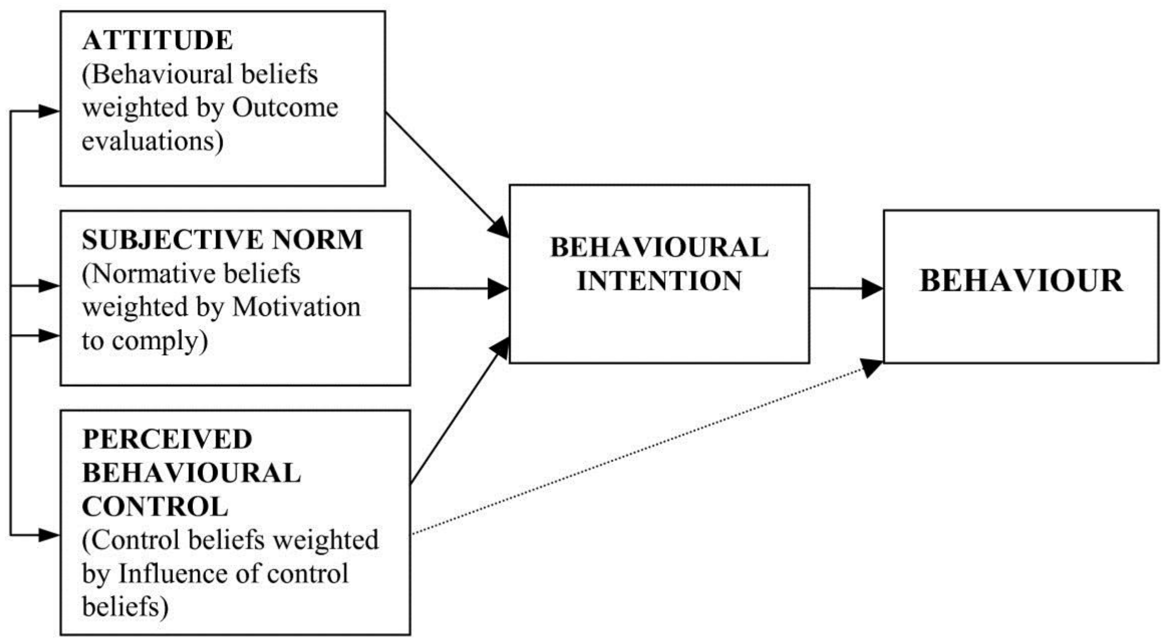

Figure 1.10: The Theory of Planned Behaviour (Ajzen, 1985)

Concepts and constructs within the frameworks

As previously stated, eighty-two distinct theoretical frameworks have been identified (Davis et al., 2015) which contain a wide variety of theoretical constructs. Whilst some are unique to specific models, many contain identical and overlapping constructs due to the development of these frameworks from common theoretical origins (Armitage and Christian 2003, Noar and Zimmerman 2005). The large number of frameworks available, and the high commonality between the constructs, presents a challenge to researchers and practitioners in knowing which framework to select and how to apply when conducting research or designing interventions (Cane, O'Connor and Michie, 2012). In response to this identified difficulty, Michie et al. (2005) developed the Theoretical Domains Framework (TDF) which (1) deconstructed each of the theoretical frameworks into distinct constructs, (2) identified duplicated constructs and (3) grouped these constructs into domains. Fifteen domains were identified, these are:

1. Skills
2. Knowledge
3. Cognitive and interpersonal skills
4. Memory, Attention and Decision Processes
5. Behavioural Regulation
6. Environmental Context and Resources
7. Social influences
8. Social/Professional Role and Identity
9. Beliefs about Capabilities
10. Optimism
11. Beliefs about Consequences
12. Intentions
13. Goals
14. Reinforcement
15. Emotion

The TDF is utilised in the research chapters of this thesis as the foundation for the hypothesised relationships between the explanatory and outcome variables of interest.

How have these frameworks been applied in obesity research?

The eighty-two theoretical frameworks outlined by Davis et al. (2015) and the TDF (Michie et al., 2005) are most often used in examinations of why individuals lose or do not lose weight (Kashima and Gallois 1993, Ajzen 1998) and in predictive analyses of weight loss outcomes (Taylor et al., 2006). These theoretical frameworks also provide a structure upon which interventions can and have been built. Examples of the application of the theory of planned behaviour to the development of weight management interventions includes Armitage (2002), Kothe, Mullan and Amaratunga (2011), Kothe, Mullan, and Butow (2012) and Wong and Mullan (2009). Further,

Limitations of the use of these frameworks for intervention design

We outline four limitations of the use of theoretical frameworks for intervention design

(1) They don't include the wider determinants of health.

Previously discussed was the importance of understanding and addressing the wider determinants of obesity i.e. factors which effect weight loss beyond the individual. A review of the use of four commonly used frameworks[4] for health-related behaviour change concluded that none of the theoretical frameworks evaluated adequately reflect the significance of social, economic and/or environmental factors as predictors or determinants of health behaviour (Taylor et al., 2006). In the context of weight management the lack of

[4] Theory of Reasoned Action, Theory of Planned Behaviour, Transtheorectical Model and Health Belief Model.

these wider determinants may result in the design of interventions that fail to adequately provide individuals with the capacity to match the complexity of the system.

(2) They don't adequately predict health behaviours.

Partly due to the lack of inclusion of the wider determinants, there are doubts regarding the ability of the frameworks to adequately predict behaviour. Meta-analytical and systematic review evidence indicates that the Theory of Reasoned Action is able to explain around 34%; the Health Belief Model 24%; and the Theory of Planned Behaviour between 20% to 30% of the observed variance in reported adult health behaviours (Zimmerman and Vernberg, 1994, Godin and Kok, 1996; Armitage and Conner, 2001; Hagger et al., 2002 and Sutton, 1998). A proposed explanation of the inability of these frameworks to accurately predict behaviour is that they are based on an assumption of rational behaviour. This, in part, may explain findings that such frameworks are able to accurately predict behavioural intention but not, however, observed behaviour (Taylor et al., 2006). Reflecting on Figure 1.10, which presents the structure of the Theory of Planned Behaviour, we clearly observed that the three constructs ('attitude toward behaviour', 'subjective norms' and 'perceived behavioural control') feed into the 'behavioural intention' construct which in turn explains behaviour. It is argued that the structure of this framework, perhaps, puts too much weight on intention as a driver of behaviour.

(3) They do not increase the effectiveness of weight management interventions

Three reviews have compared the outcomes of weight management interventions developed utilising a specified theoretical framework against the outcomes of interventions developed using a generic approach to design (Gardner et al., 2011; Roe et al., 1997;

Ammerman et al., 2002 and Bhattarai et al., 2013). All three reviews find no association between interventions utilising specified theoretical frameworks and those that do not. Specifically, a recent Cochrane review (Cochrane, 2014) identified three studies which compared the outcomes of weight management programmes developed using the transtheoretical model against weight management programmes developed using a generic approach. All three studies utilised a randomised controlled trial (RCT) design. The review concluded that the interventions utilising the transtheoretical model are no more likely to be effective than alternative designed interventions in achieving in sustained weight loss. These finding have led to both narrative and systematic reviews concluding that intervention effectiveness is unrelated to the use of these theoretical frameworks at the development stage of weight management interventions (Hardeman et al., 2002).

(4) They may increase health inequalities

The lack of social, environmental and economic factors and the overreliance on the assumption of rational behaviour have led some to argue that, as health inequalities "*are functions of material and social differences, interventions based primarily on changing individual cognitions would be unlikely to eliminate such disparities*" (Taylor et al., 2006). There is a requirement for theoretical frameworks of individual behaviour to reflect the wider determinants of obesity and relax assumptions of rationality if they are to be successful in both predicting behaviour and supporting behavioural change.

What are the proposed alternative approaches to integrate theory into practice?

Clearly there are major problems with the use of theoretical frameworks as the foundation for weight management intervention design. NICE, correctly, continues to recognise the significant importance of the integration of theory into practice and recommends that approaches should "*use proven behaviour change techniques when designing interventions*". This alternative approach, in essence, moves away from the use of theoretical frameworks (which claim to explain behaviour in its entirety), to the use of individual behaviour change techniques that have been proven empirically to increase the probability of weight loss. Empirical examinations of the effectiveness of behaviour change techniques within weight management programmes can be found in Hartmann-Boyce et al. (2014) and Dombrowski et al. (2012). The evidence in these reviews has contributed to formal guidance on the use of behaviour change techniques within behaviour change and weight management interventions. The specific behaviour change techniques recommended within NICE guidance (NICE, 2014 and NICE, 2014a) are outlined in Table 1.5.

BCT Domain	BCT Technique	Description
Antecedents	Changes the social environment	Change, or advise to change the social environment in order to facilitate performance of the wanted behaviour or create barriers to the unwanted behaviour (other than prompts/cues, rewards and punishments).
Feedback and monitoring	Self-monitoring	Establish a method for the person to monitor and record their behaviour(s) as part of a behaviour change strategy.
Goals and planning	Goal setting (behaviour)	Set or agree on a goal defined in terms of the behaviour to be achieved.
	Goal setting (outcome)	Set or agree on a goal defined in terms of a positive outcome of wanted behaviour.
	Review behaviour goals	Review behaviour goal(s) jointly with the person and consider modifying goal(s) or behaviour change strategy in light of achievement. This may lead to re-setting the same goal, a small change in that goal or setting a new goal instead of (or in addition to) the first, or no change.
	Problem solving	Analyse or prompt the person to analyse, factors influencing the behaviour and generate or select strategies that include overcoming barriers and/or increasing facilitators.

Shaping knowledge	Behavioural instruction	Advise or agree on how to perform the behaviour.
Social support	Social support (general)	Advise on, arrange or provide social support (e.g. from friends, relatives, colleagues or staff) or praise or reward for performance of the behaviour. It includes encouragement and counselling, but only when it is directed at the behaviour.
	Social support (practical)	Advise on, arrange, or provide practical help (e.g. from friends, relatives, colleagues or staff) for performance of the behaviour.
	Social support (emotional)	Advise on, arrange, or provide emotional social support (e.g. from friends, relatives, colleagues or staff) for performance of the behaviour.
	Feedback on behaviour	Monitor and provide informative or evaluative feedback on performance of the behaviour (e.g. form, frequency, duration, intensity).
	Feedback on outcome	Monitor and provide feedback on the outcome of performance of the behaviour.

Table 1.5: Behaviour Change techniques drawn from NICE (2014) and NICE (2014a).[5]

[5] The framework for the identification of behaviour change techniques is the Behaviour Change Technique (BCT) Taxonomy (Michie et al., 2011). Descriptions of the Behaviour Change techniques are taken also from Michie et al., 2011.

What are the limitations of this alternative approach?

There are several criticisms of this proposed alternative approach of the integration of individual behaviour change techniques into weight management interventions.

Correlational analyses used to examine the estimated weight loss resulting from the inclusion of specific behaviour change techniques within weight management interventions (Hartmann-Boyce et al., 2014 and Dombrowski et al., 2012) are problematic. The approach of these analyses is to identify RCTs of weight management intervention and code the behaviour change techniques used in each arm of the identified trials. The fact that the behaviour change techniques are not randomly allocated to trial arms means they are confounded with other features of the intervention design including the presence of other behaviour change techniques. It is therefore difficult to disentangle the exact influence of the individual behaviour change techniques on outcomes. As the NICE guidance for the inclusion of specific behaviour change techniques is made on the foundations of the findings of such studies, this perhaps raises questions on the validity of such recommendations. Discussions reveal a further limitation of recommendations of individual techniques, in that, such approaches do not reflect the complexity of weight management interventions, for example, they present no evidence regarding how the intensity or combination of behaviour change techniques impacts outcomes.

The behaviour change techniques within current discussion are identified using the Behaviour Change Technique (BCTT) Taxonomy (Michie et al., 2011). The BCTT is a synthesis of techniques which have been drawn from empirical studies. This method of identification has resulted in a non-comprehensive taxonomy with no reflection of prospective approaches to behaviour change. The method by which the taxonomy was developed also raises a further, and critical, limitation of the approach. As the techniques are drawn from empirical studies, whilst they may predict behaviour change, they lack an understanding of why behaviour is affected. In essence, they lack specified theoretical foundations and, therefore, do not provide researchers and practitioners with an understanding of the mechanism(s) of action. This disconnect from theory is summarised by Harrison (2013) who argues that "*if we are to design normative policies, and understand the opportunity cost of doing so, we need to understand why we see certain behaviour*". Within the context of weight management research we cannot expect to accurately predict behaviour if we do not understand preferences or beliefs. In the context of weight management interventions, to expect consistent behavioural change as a result of the integration of a specified behaviour change technique, we must rely on assumptions of consistencies in the beliefs and preferences of individuals. Given the influential nature of contextual factors, this discussion raises questions regarding whether such assumptions can be upheld.

Further, Harrison (2013) proposes that policy based on identifying which interventions demonstrate the most positive average effect may, in fact, result in increasing health inequalities if they do not account for intra-distributional effects. Within the current context, the recommended behaviour change techniques are based on studies reporting the average expected weight change resulting from the inclusion of the techniques within weight management progammes. Harrison (2013) argues that if the underlying probability distribution is, for example, bimodal, the average effect may look positive, however, the intra-distributional effects may indicate a clear divide between those for which the intervention was success and those for whom it was not. Harrison (2013) concludes that:

"*There is an important and direct theoretical reason for wanting to keep track of the intra-distributional effects: we care a lot about 'winners' and 'losers' from policy. No policy-maker can afford to ignore these equity effects, and if it is at all possible to come up with policy alternatives that mitigate losses, that is usually extremely attractive.*" In the context of weight management there is a requirement to, at the least, be able to identify who interventions are working for, thereby allowing the development of policy to minimise losses.

The criticisms of the use of behaviour change techniques have been recognised by the researchers who originally developed the BCTT. Their response has been to map behaviour change techniques to theoretically founded mechanisms of action (Michie et al., 2016). For example it is suggested that the behaviour change technique "feedback on behaviour" (see Table 1.5) is underpinned by the theoretical construct "subjective norms" (Michie et al., 2016). Much of this research is yet to be published, thus, our discussion present the most current approach to the application of (largely psychological) theory to weight management practice.

Discussions clearly demonstrate a desire for the application of theory to weight management programmes and a need to understand why individuals behave the way they do. Partly for this reason there has been a recent but growing interest in the use of behavioural economics in policy which, we argue, current theoretical models of behaviour would benefit from including.

The popularity of behavioural economics is, in part, due to the discipline's acknowledgement of the limitations of modelling behaviour based on assumptions of rational decision making (Sampson, 2015). A limitation of the conventional economic approach is that it assumes that obesity is a result of individual choice i.e. that obesity is a result of a deliberate decision by an individual to favour overconsumption and sedentary behaviour over the health benefits of weight loss (Murphy, 2006 and Downs and Loewenstein, 2011). Kahneman (2011) introduced the idea that behaviour is a result of two systems; one fast and automatic, the other slow and deliberate (Kahneman, 2011). The distinction is important as it provides a theoretical basis for why the rational decision model may not accurately predict behaviour, particularly as it is suggested that our behaviour is largely a product of the automatic system which is effortful to override (Kahneman, 2011). Broadly, behavioural economics challenges three assumptions; (1) unbounded rational, (2) unboundedly willpower and (3) unbounded selfishness (Thaler and Mullainathan, 2008). In the case of obesity, it is not to say that the rational choice perspective has not successfully demonstrated the importance of a number of factors associated with obesity, such as the impact of food prices and income (Crawley, 2011), however, due to the assumptions outlined above, it cannot always explain the important factors outlined in the complex system map (Downs and Loewenstein, 2011).

One such concept from behavioural economics which has particular relevance to obesity is time discounting (Frederick, Loewenstein, & O'Donoghue, 2002). Time discounting research investigates differences in the relative valuation placed on rewards at different points in time, by comparing its valuation at an earlier date with one for a later date (Frederick, Loewenstein, & O'Donoghue, 2002). The findings from such research show that present rewards are often weighted more heavily than future ones. In the context of obesity this could be the higher value placed on unhealthy consumption and physical inactivity compared to better health in the future (Lui, 2014). Chapter 5 of this thesis explores the relationship between time preference (and risk preference) and BMI.

A further example relevant to the impact of the environment on obesity is the effect of visceral factors on obesity (Downs and Loewenstein, 2011). Visceral factors can be thought of as our primal drivers of behaviour such as hunger, thirst, craving to addictive substances and emotion (Loewenstein, 1996). In the context of obesity, visceral factors are stimulated by exposure to cues in the environment, such as the sight or smell of food, which cause individuals to respond to short-term consumption desires, overriding longer-term interests in health (Liu et al., 2014). One example of the effect of visceral factors in a controlled setting is a study by Fedoroff, Polivy and Herman (2003) which exposed restrained and unrestrained eaters to the smell of either pizza, cookies, or no smell and were then presented with either pizza or cookies to eat and review. Following exposure to food cues restrained eaters exhibited a significantly different response to exposure to food cues whereby they ate significantly more than unrestrained eaters (Fedoroff, Polivy and Herman, 2003). This idea that some individuals are more vulnerable to exposure to cues is reflected by Foreward et al. (2015). In this study, however, individuals were exposed to adverts designed to increase healthy eating. Interestingly following exposure to the advert, more educated individuals ate more fruit than their less education counterparts (Foreward et al., 2015). Whilst presenting just two studies, they are useful to highlight the notions presented previously of the differing vulnerabilities of individuals to factors in the environment and the limitation of the rational decision model that simply providing more information will result in rational, healthier decision making. Of interest from a policy perspective is both a need to reduce exposure to unhealthy food cues and the need to understand the effectiveness of policy interventions, such as information provision in the context of obesity inequalities. In the context of this research it is suggested that individuals who require weight loss (e.g. restrained eaters) and individuals with factors more probable of experiencing obesity (e.g. lower education) may require more intensive support, such as that provided by behavioural weight management programmes, to provide adequate capacity to match the complexity of the environment.

Of importance to current discussions is that of the stigmatisation of weight status. The concept of the stigmatisation of weight refers to the discrimination and unfair treatment of individuals due to classifications of overweight and obesity. This concept is of particular relevance to current discussions as stigmatisation, in part, results from a misunderstanding of obesity as a consequence of choice as per the rational choice perspective. By moving away from this unhelpful perspective, behavioural economics contributes to efforts to shift these cultural perceptions of obesity.

The prevalence of stigmatisation of weight is high (Moskovich, Hunger and Mann, 2011). Approximately 5% and 10% of overweight men and women respectively have experienced weight discrimination on a daily basis. Amongst obese men and women this increases to 28% and 45% respectively (Puhl, Andreyeva and Brownell, 2008). A key concern is the strong evidence that stigmatisation exasperates obesity by negatively impacting individual's psychological (Hatzenbueler, Keys and Hasin, 2009) and physical health (Maclean et al., 2009).

Whilst overweight individuals face discrimination in the employment setting (Polinko and Popovitch, 2001; Roehling et al., 2008; Puhl and Brownell., 2006 and Puhl and Haurer., 2009), the educational setting (Puhl and Latner., 2007) and in a customer service setting (King et al., 2006), of particular interest in the context of the research presented in this thesis is discrimination faced in the health service. Weight status stigmatisation and misunderstanding of the causes of obesity permeating the medical profession, whereby, Foster et al. (2003) reports that over half of clinical practitioners described obese patients as weak-willed and lazy (Forster et al., 2003). Whilst this particular study is based in the US it can be assumed that this issue translates, at least to some extent, to the UK. Referral to the behavioural weight management programme evaluated in this thesis is via a healthcare professional, such as a General Practitioner (GP) or Practice Nurse. If obese individuals identify the healthcare setting as a source of discrimination it may lead patients to avoid or delay seeking treatment (Moskovich, Hunger and Mann, 2011 and Drury and Louis, 2002). Whilst our research does not explore this stage of the referral process statistical analysis of referral rates of health practitioners based on expected demand could expose potential areas of concern. Turning discussions to the weight management provider, Slimming World, all consultants are previous Slimming World participants and, thus, a significantly lower prevalence of weight status stigmatisation is expected. In the context of this discussion the consultants are indeed a strength of the approach.

A further discussion of relevance is the stigmatising effect of public policy (Kresh and Morone, 2011). Policy maker face a difficulty in how to respond to obesity. On one hand, promoting solutions to obesity may increase stigmatisation whilst not publically acknowledge the issue may worsen the situation (Kresh and Morone, 2011). Policies supported theoretically and empirically by behavioural economics have tended to favour approaches which address the obesogenic environment and policies tackling the wider determinants of health and, thus, avoid the potentially harmful effects of policies designed to address obesity alone (Kresh and Morone, 2011).

Downs and Loewenstein (2011) provide an introduction to obesity from a behavioural economics perspective and outline a number of concepts in addition to present-biased preferences and visceral effect. They include willpower, intangibility, projection bias, narrow decision bracketing, diminishing sensitivity and motivated information processing (Downs and Loewenstein, 2011).Whilst this section will not discuss each concept in detail it highlights the increasing contribution of behavioural economics to the understanding of causes of obesity.

As previously stated, research utilising the behavioural economic concept of time preference in the context of obesity is presented in Chapter 5. The influence of the behavioural economics approach is, however, reflected throughout this thesis.

Behavioural economics provides a ‘lens’ through which the findings of the research in this thesis can be interpreted. It reflects the gaps in current behaviour change theory which often neglects the impact of the wider environment on behaviour. Further, by presenting a theoretical basis for the automaticity of decision making, behavioural economic research can also demonstrate the variability in individual vulnerability to factors in the environment. It also acknowledges the previous overreliance on assumptions of rationality within theoretical, empirical and political discussions which may have led to the implementation of sub optimal behaviour change recommendations.

A second reason for the growing popularity of behavioural economics is the rigorous methodological approaches. Behavioural economics recognises the value of psychology to provide the theoretical foundations for deviations from the assumption of rational decision making and then applies robust methodological approaches typical in the economics discipline to model and evaluate these behavioural insights. This philosophy is reflected in this dissertation whereby a psychological perspective has been taken to understanding weight loss and retention in behavioural weight management programmes with sophisticated economic models deployed to provide robustness to methodologies.

To conclude this section we provide a summary of discussions: A single behaviour change model to develop effective behavioural weight management programmes has not been identified. There is however, good evidence for the use of some specific behaviour change techniques which are outlined in NICE guidance. Despite this there is a requirement for existing behaviour change frameworks to be able to reflect the complexity of obesity and this in part can be achieved through the integration of behavioural insights from the behavioural economics discipline. Finally, behavioural economics is reflected throughout this thesis whether it is in the exploration of concepts or application of approaches unique to the discipline.

1.7.4 Are Behavioural Weight Management Programmes Successful?

Protocols are available for two anticipated evidence reviews;

(1) The Cochrane Review (*"Interventions for treating overweight or obesity in adults: an overview of systematic reviews*") (Roqué i Figuls et al., 2013) and
(2) the Evidence for Policy and Practice Information and Co-ordinating Centre (EPPI) Review *("What makes a successful weight management programme- A systematic review of programme components and a descriptive analysis of current provision in England")* (EPPI, 2016).

These are likely to represent the gold standard for evidence of effectiveness in behavioural weight management programmes. As they are not yet published, this section presents the best available evidence for the effectiveness of such programmes.

Chapters 2 and 3 present discussions on the effectiveness of behavioural weight management programmes at a sub-group level. The following section, therefore, presents the evidence for overall effectiveness. This first section looks specifically at outcomes resulting from the service. The findings will be set in the context of the NICE recommendations for outcomes i.e.:

- Average weight loss among patients is greater or equal to 3%.
- 30% of patients loose greater or equal to 5% of their original body weight.

Teixeria et al. (2005) published a comprehensive review of literature exploring weight loss services. The literature summary table presented by Teixeria et al. (2005) has been adapted and expanded here to include further relevant research. Excluded from this search were studies of surgical, paediatric, post-partum and pharmacological weight loss interventions. In total 49 studies were identified and included, the results of this exercise are presented in Table 1.6.

	Sample					Analysis			
Reference	n	Male (%)	Age (mean)	BMI (mean)	Country	Statistical Methods	Length	Outcome measure	Result
Bryan and Tiggemann (2001)	42	0	49	34	Australia	ANOVA (Analysis of Variance)	12 weeks	Weight reduction at week 12	-7.9kg
Cuntz et al. (2001)	138	-	-	~46	Germany	T-tests and Pearson correlation coefficients (PCC)	10 weeks	Weight change at week 10	-6.9kg
Delahanty et al. (2013)	274	35	53	(95kg)	USA	Logistic regression	6 months	% of individuals losing ≥7% of initial weight lost at 6 months	52%
Dennis and Goldberg (1996)	109	0	45	31	USA	ANOVA and MANOVA (Multivariate Analysis of Variance)	9 months	Weight loss at 3 months	6.80%
	109	0	45	31	USA	ANOVA and MANOVA	9 months	Weight loss at 6 months	9.70%
Drapkin, Wing and Shiffman (1995)	93	35	52	37.3	USA	ANOVA	12 months	Weight change at 12 months	-12kg
Eldredge and Agras (1997)	47	4		38.6	USA	Regression	9 months	Weight loss at month 9	-3kg
Elfhag and Rössner (2010)	247	29	42	41.1	Sweden	Linear regression	6 months	Weight change after 5 weeks	-1.1kg
	247	29	42	41.1	Sweden	Linear regression	6 months	Weight changes 4-5 months	-6kg
Fabricatore et al. (2009)	224	20	44	37.8	USA	Logistic regression	1 year	% of individuals losing ≥5% of initial weight lost in 1 year	52.20%
Fogelholm et al. (1999)	85	0	-	34	Finland	ANOVA	12 weeks	Weight change at week 12	-13.5kg
Fontaine and Cheskin (1997)	109	35	44	42	USA	Correlation	0-34 weeks	Weight reduction at last record	-30.7lbs
Fontaine and Cheskin (1999)	177	34	44	42	USA	Correlation	0-33 weeks	Weight reduction at last record	-30.6lbs
Foster et al. (1998)	223	0	41	37.2	USA	ANOVA and correlations	12-16 weeks	Weight change at 5-6 months	-16.7kg
Gladis et al. (1998)	118	0	41	36.3	USA	ANOVA and ANCOVA (Analysis of Covariance)	48 weeks	Weight loss at week 8	-10.3kg
	118	0	41	36.3	USA	ANOVA and ANCOVA	48 weeks	Weight loss at week 17	-14.2kg
	118	0	41	36.3	USA	ANOVA and ANCOVA	48 weeks	Weight loss at week 24	-17.1kg
	118	0	41	36.3	USA	ANOVA and ANCOVA	48 weeks	Weight loss at week 48	-14.6kg
Gripeteg et al., 2010	267	34	40	43.1	Sweden	Multivariate logistic regression	12 weeks	% weight loss at week 12	14.0%

Handjieva-Darlenska et al. (2012)	771	M/F	37	35.6	Various (Europe)	Multiple regression	10 weeks	Weight change week 10	-6.8kg
Heshka et al. (2003)	423	15	45	33.7	USA	ANCOVA	12 weeks	Weight change year 1	-4.3kg
	423	15	45	33.7	USA	ANCOVA	12 weeks	BMI change year 1	-1.6
	423	15	45	33.7	USA	ANCOVA	12 weeks	% of individuals losing ≥5% of initial weight lost after 1 year	29.2%
	423	15	45	33.7	USA	ANCOVA	12 weeks	Weight change year 2	-2.9kg
	423	15	45	33.7	USA	ANCOVA	12 weeks	BMI change year 2	-1.1
	423	15	45	33.7	USA	ANCOVA	12 weeks	% of individuals losing ≥5% of initial weight lost after 2 years	27.3
Hollis et al. (2008)	1,685	33	55	34.3	USA	Regression	20 weeks	Weight change at 6 months	-5.8kg
	1,685	33	55	34.3	USA	Regression	20 weeks	% of individuals losing ≥4kg at 6 months	69%
Gokee-LaRose et al. (2009)	40	12	29	33.4	USA	ANOVA	10 weeks	Weight change at week 10	-6.3kg
	40	12	29	33.4	USA	ANOVA	10 weeks	Weight change at week 20	-6.2kg
Jeffery et al (1998)	130	53	38	30.9	USA	Chi-squared tests (χ^2-tests)	18 months	Achieves personal weight goal	15%
Karlsen, Søhagen and Hjelmasæth (2013)	199	29	45	42	Norway	Multiple linear regression	1 year	Weight change during 1 year treatment	-10.0kg
	199	29	45	42	Norway	Multiple linear regression	1 year	% weight change during 1 year treatment	-8.00%
Kayman, Bruvold, and Stern (1990)	108	43	0	-	USA	Descriptive	1 year	Study of weight relapse and maintenance	-
Kiernan et al. (1998)	177	50	-	29	USA	Signal detection methods	1 year	Lose 2 BMI points during the year	37.70%
Kong et al. (2010)	51	45	51	40.5	Canada	Logistic regression	1 year	% of individuals losing ≥5% of initial weight lost in 1 year	51%
Leibbrand and Fichter (2002)	109	16	37	44.8	Germany	T-tests and ANOVA	10 weeks	Weight loss at week 10	-7.0kg
	109	16	37	44.8	Germany	T-tests and ANOVA	10 weeks	Weight loss at 6 months	-8.0kg
Linde et a. (2005)	1,226	19	35	27.2	USA	MANOVA	Various	BMI change 12 months	+0.26
	1,800	28	51	34.2	USA	MANOVA	Various	BMI change 12 month	-0.53
	1,226	19	35	27.2	USA	MANOVA	Various	BMI change 24 months	0.50
	1,800	28	51	34.2	USA	MANOVA	Various	BMI change 24 month	-0.48
Linné et al. (2002)	100	43	40 (med.)	40.7	Sweden	Wilcoxen's test	11 weeks	% of individuals losing ≥5% of initial body weight at 6 months	35%

Liu et al. (2013)	1,566	-	-	-	USA	-	6 months	% of individuals losing ≥5% of initial body weight at 6 months	42.7%
Munro et al., 2011	54	26	42	32.7	Australia	ANOVA and multiple regression	12 weeks	% of individuals losing ≥5% of initial weight lost by the end of the intervention	65%
Nir and Neumann (1995)	66	0	-	30	Israel	-	10 weeks	Weight change following intervention	+3.1kg
Ortner- Hadžiabdić et al. (2014)	124	26	48	41.6	Croatia	Logistic regression	1 year	% of individuals losing ≥5% of initial weight lost in 1 year	33.10%
Pasman and Saris (1999)	67	0	38	32.1	The Netherlands	T-tests and correlation	2 months	Weight change at 2 months	-9.7kg
Pekkarinen, Takala and Mustajoki (1996)	62	8	41	36.4	Finland	ANOVA, Correlation and linear regression	17 weeks	Weight change at week 17	-14.9kg
Carlos-Poston et al. (1999)	102	22	43	39	USA	Linear regression	8 weeks	BMI reduction at 3 months	-10.6
Raymond et al (2002)	174	0	39	~36	USA	ANOVA	24 weeks	Weight change at week 24	-17kg
Sacks et al. (2009)	811	36	51	33.0	USA	T-tests	2 years	Weight change at 6 months	6kg
	811	36	51	33.0	USA	T-tests	2 years	Weight change at 6 months	7%
Sherwood, Jeffery and Wing (1999)	444	0	40	~31	USA	Chi-squared tests (χ^2-tests)	18 months	Weight loss at week 26	-8kg
	444	0	40	~31	USA	Chi-squared tests (χ^2-tests)	18 months	Weight loss at week 78	-4kg
Smith et al. (1995)	54	0	38	32	USA	Multiple regression	15 weeks	Weight loss at week 15	-10lbs
Smith, O'Neil and Rhodes (1999)	289	0	41	34.7	USA	ANCOVA and MANCOVA	20-30 weeks	Weight change at end of intervention	-11.0kg
	289	0	41	34.7	USA	ANCOVA and MANCOVA	20-30 weeks	% weight change at end of intervention	-10.90%
	289	0	41	34.7	USA	ANCOVA and MANCOVA	20-30 weeks	BMI change at end of intervention	-4
Teixeria et al. (2002)	112	0	48	31.4	USA	Multiple regression	16 weeks	Weight loss at week 16	-5.4kg
	112	0	48	31.4	USA	Multiple regression	16 weeks	% weight loss at week 16	-3.40%
Teixeria et al. (2004)	140	0	38	30.3	Portugal	Bivariate and multivariate correlation/regression	4 months	Weight loss at 4 months	-3.0kg
	140	0	38	30.3	Portugal	Bivariate and multivariate correlation/regression	4 months	% of individuals losing 3.3% of initial body weight	53%

Teixeria et al., (2004)	158	0	48	31	USA	Logistic regression	16 weeks	Weight loss at week 16	-5.1kg
	158	0	48	31	USA	Logistic regression	16 weeks	% weight loss at week 16	-6.20%
	158	0	48	31	USA	Logistic regression	16 weeks	Weight loss at 16 months	-4.6kg
	158	0	48	31	USA	Logistic regression	16 weeks	% weight loss at 16 months	-5.50%
Traverso et al. (2000)	50	24	40	33.2	Italy	-	23 weeks	Weight loss at week 23	-11.3kg
VanWormer et al. (2009)	100	9	47	38.4	USA	Regression and interaction effect	6 months	Weight loss 6 months	-5.5lbs
	100	9	47	38.4	USA	Regression and interaction effect	6 months	% of individuals losing ≥5% of initial body weight (6 months)	27%
	100	9	47	38.4	USA	Regression and interaction effect	6 months	Weight loss 6 months	-4.4lbs
	100	9	47	38.4	USA	Regression and interaction effect	6 months	% of individuals losing ≥5% of initial body weight (12 months)	19%
Wadden et al. (1992)	76	0	42	39.4	USA	Correlation	5-7 months	Weight change at 1 month	-3.6kg
	76	0	42	39.4	USA	Correlation	5-7 months	Weight change at end of treatment	-14.5kg
	76	0	42	39.4	USA	Correlation	5-7 months	Weight change at 1 year	-7.7kg
Welsh et al. (2009)	63	21	50	34.2	USA	Linear Regression	6 months	Weight change at 6 months	-4.4kg
Westerterp-Plantenga, Kempen and Saris (1998)	57	0	<19	31	The Netherlands	ANOVA and regression	8 weeks	Weight change at week 8	-10.7kg
Williams et al. (1996)	128	27	43	41	USA	Correlation and maximum likelihood	6 months	BMI change at 6 months	-8.2
Wiltink et al. (2007)	267	15	41	44		ANOVA, t-tests, and multiple regression and chi-square test	6-10 weeks	BMI change at year 3	-1
Wing and Jeffery (1999)	166	49	43	31.2	USA	Chi-squared tests (χ^2-tests)	16 weeks	Weight loss at week 16	-7.9kg

Table 1.6: Summary of the literature exploring predictors of weight loss outcomes

The first observation is the huge heterogeneity in weight loss outcome utilised in the identified studies. Of the 49 studies, only 15 can be assessed against one of the NICE criteria. This is largely due to the tendency to report the effect of the intervention as absolute weight loss (either KGs or lbs).

Table 1.7 categorises the fifteen studies by the NICE criteria evidenced and whether the criteria are met. Of the fifteen identified studies only two present results which do not meet the NICE recommendations. This may, of course, be due to a publication bias for the studies with significant results; however, it does provide evidence that at least in the short term (i.e. the period over which the service is delivered) weight management approaches can be described as successful.

Further, large scale evaluations of outcomes in the two largest providers of weight loss services in the UK (Slimming World and Weight Watchers) found that, among completers, average percentage weight loss is 5.5% and 5.6% respectively and the percentage achieving greater than or equal to a 5% reduction in initial body weight is 55% and 57% respectively (Stubbs et al., 2011 and Ahern et al., 2011).

In the context, therefore, of the first two NICE recommendations there is fairly good evidence of an ability of behavioural weight management programmes to achieve significant outcomes.

	Meets the NICE criteria	Does not meet the NICE criteria
Average weight loss among patients is greater or equal to 3%.	Gripeteg et al., 2010 Karlsen, Søhagen and Hjelmasæth (2013) Sacks et al. (2009) Smith, O'Neil and Rhodes (1999) Teixeria et al. (2002) Teixeria et al., (2004)	-
30% of patients loose great or equal to 5% of their original body weight.	Delahanty et al. (2013) Fabricatore et al. (2009) Kong et al. (2010) Linné et al. (2002) Liu et al. (2013) Munro et al., 2011 Ortner- Hadžiabdić et al. (2014)	Heshka et al. (2003) VanWormer et al. (2009)

Table 1.7: Identified studies mapped to the NICE guidance criteria for behavioural weight management programmes.

Longer Term Effectiveness

The third weight related criterion set out in the NICE guidance is the ability for services to demonstrate effectiveness at 12 months or beyond. Slightly unhelpfully, the guidance does not outline a specified weight reduction outcome for this longer term objective; however, conclusions of comprehensive reviews have found behavioural weight management programmes demonstrate small but significant benefits on weight loss maintenance (Dombrowski et al., 2014 and Brown et al., 2009).

A difficulty in assessing longer-term outcomes is the huge variation in the length and intensity of interventions. From Table 1.6 we observe interventions that provide support for up to 18 months (Sherwood, Jeffery and Wing,1999) with others delivering interventions for as little as 6 weeks (Wiltink et al., 2007)). Further heterogeneity in intervention design means that some interventions simply provide a weight loss service, whereas others provide a weight loss service followed by a weight maintenance service. The resulting limitation of this heterogeneity is the inability to decipher whether the initial weight loss intervention alone has provided the necessary capacity to maintain lost weight. A key question to be addressed is, therefore, what happens to individuals' weight following services where weight maintenance support is not tangibly provided?

Amongst the 49 studies outlined in Table 1.6, 11 report results at 1 year or beyond; all report some level of weight loss[6]. Of these 11 studies only 4 represent studies which have recorded participants' weight after a period of time without access to the weight loss

[6] Sherwood, Jeffery and Wing (1999), Ortner- Hadžiabdić et al. (2014), Linde et a. (2005), Kong et al. (2010), Kiernan et al. (1998), Kayman, Bruvold, and Stern (1990), Karlsen, Søhagen and Hjelmasæth (2013), Jeffery et al (1998), Heshka et al. (2003), Fabricatore et al. (2009) and Drapkin, Wing and Shiffman (1995).

service or explicit weight maintenance support (Heshka et al., 2003; VanWormer et al., 2009; Wadden et al., 1992 and Wiltink et al., 2007).

From a policy perspective, whilst the outcomes of trials contained in Table 1.6 are of interest, of importance is the assurance that services which are most frequently accessed and commissioned meet the standards outlined by NICE. To this effect, there is strong trial evidence that Slimming World (SW) and Weight Watchers (WW), the two largest providers in the UK, are effective at 12 to 18 months (NICE, 2014). This conclusion from NICE is based on the pooled results of three studies from which the 12 and 24 month weight outcomes have been extracted and presented in Table 1.8.

		Jolly et al. (2011)	Jebb et al. (2011)	Heshka et al. (2003)	
Weight Watchers	Time Period	1 year	1 year	1 year	2 years
	Mean (kg)	-4.4kg	-6.6kg	-4.3kg	-2.9kg
	% achieving ≥5% weight loss	31%	46%	29%	27%
Slimming world	Time Period	1 year	-	-	-
	Mean (kg)	-3.1kg	-	-	-
	% achieving ≥5% weight loss	21%	-	-	-

Table 1.8: Longer Term Weight Outcomes of Weight Watchers and Slimming World

The second discussion of interest to policy makers focuses on the change in individual's weight following a weight loss intervention. Whilst ideally any weight loss would be maintained over a lifetime, previous research has found that weight loss peaks at around six months, followed by a gradual regain of weight (Dombrowski et al., 2014; Avenell et al., 2004 and Dombrowski, Avenell and Sniehotta., 2010). There is a debate, therefore, about whether this initial weight loss provides any longer-term benefits. To an extent this depends on the rate, duration and, thus, the overall amount of weight regained in comparison to what would have been expected with no period of initial weight loss. A significant limitation in answering this question is the severe lack of research which reports outcomes beyond the duration of the intervention and particularly beyond a 1 to 2 year follow up period.

Amongst the general population weight, on average, increases by 0.3kg per year (NICE, 2015). Although seemingly small, over a lifetime these incremental increases accumulate to cause the obesity prevalence we currently face (NICE, 2015). A behavioural weight management programme, on average, decreases the weight of an individual by 2.6kg (NICE, 2015); therefore, even if weight change following the intervention simply reverts to reflect the 0.3kg weight gain experienced in the general population, an individual would experience approximately 9 years of reduced weight compared to baseline. This is graphical represented in Figure 1.11.

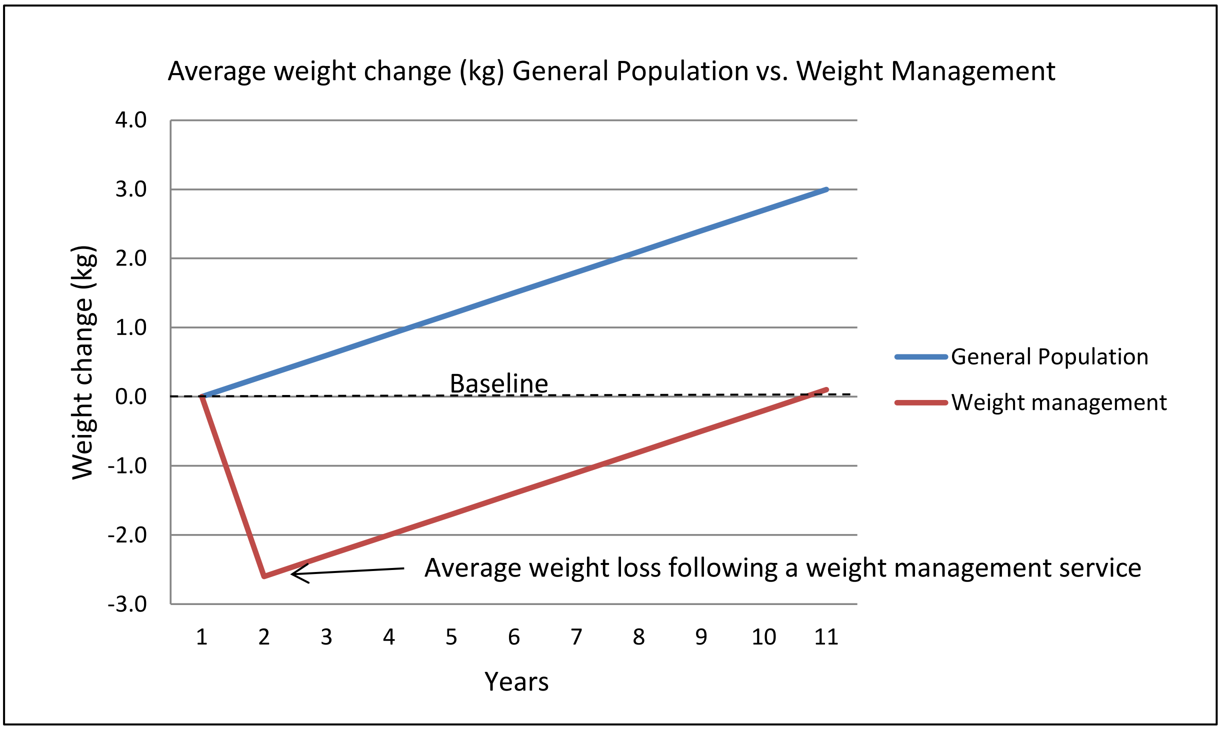

Figure 1.11: Graphical representation of continued weight reduction following a behavioural weight management programme.

There is, however, evidence that weight regain following a weight loss intervention is higher amongst individuals following a behavioural weight management programme compared to the control (Johns et al., 2013). Johns et al. (2013) present clear evidence of a 'wearing-off' of the effect of weight loss whilst also evidencing that a longer-term effect remains. See Figure 1.12.

In summary, the evidence for long term effectiveness of behavioural weight management programmes is weak due to a lack of studies reporting longer-term outcomes. The available empirical evidence does, however, indicate that the seemingly small reductions achieved by behavioural weight management programmes do have longer term benefits at a population level.

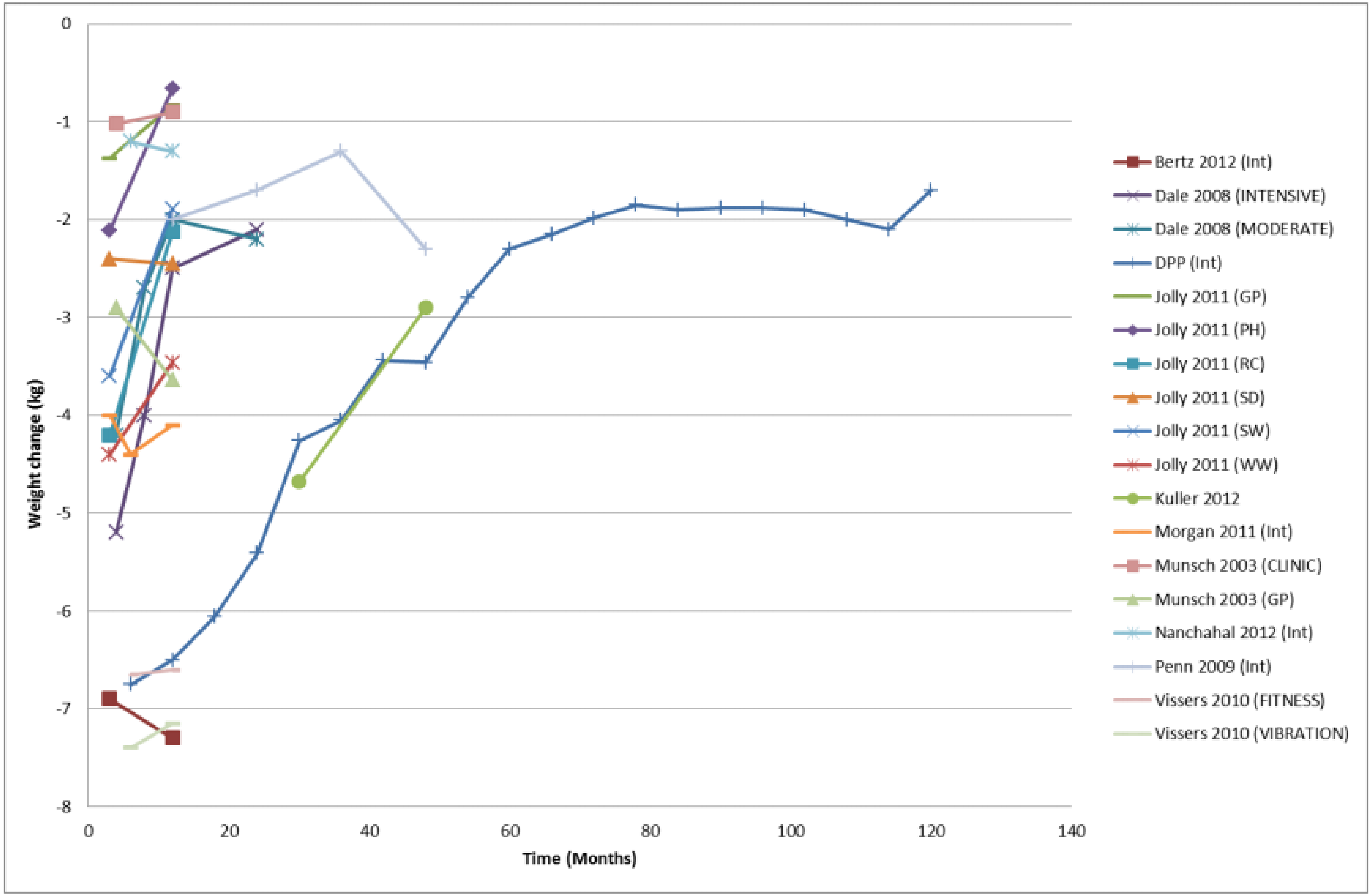

Figure 1.12: Weight regain in behavioural weight management interventions following the end of the programme (Johns et al., 2013)

Cost Effectiveness

Discussions regarding longer-term effectiveness of behavioural weight management programmes are complimented here by a brief discussion regarding the cost-effectiveness of the approach. As with examinations of longer-term effectiveness, cost effectiveness is also harboured by the severe lack of longer-term reporting of weight loss outcomes.

A further piece of NICE guidance outlines recommendations for preventing excess weight gain (NICE, 2015). Within the supporting evidence of this guidance is a report outlining the cost effectiveness of behavioural weight management programmes from a population modelling viewpoint. Representing the most robust evidence available, the findings of this report are discussed below.

There is no reliable evidence for what happens in the longer-term following a weight loss intervention and, thus, cost effectiveness is based on a number of assumptions including that small amounts of weight loss can be maintained for longer periods. The evidence is limited but seems to support this assumption (see previous discussion). Building on the findings of the section above, reductions in average BMI from behavioural weight management programmes are small but compared to the weight gains at population level they are not insignificant (NICE, 2015). Despite the limitations of the evidence NICE (2015) concludes that these approaches are cost effective if provided for no more than £100 to £500 per head. In fact the economic modelling found that as little as 1kg weight loss, if sustained, would prove to be cost effective if the intervention was provided for less than £100 per patient. The intervention evaluated in this thesis is provided at £47.50 per patient.

Whilst discussions are encouraging they highlight the importance of longer term evaluation to contribute to our understanding of effectiveness and cost-effectiveness. In the context of this research, however, such longer term outcomes will not be available.

Despite an inability to report longer-term weight outcomes there is an important issue that should be acknowledged within current discussions; the effect of weight cycling. Weight cycling refers to the cyclical process of weight loss and regain (Brownell and Rodin, 1994). Weight cycling is of relevance due to evidence presented in previous discussions regarding weight regain following behavioural weight management programmes. In theory weight cycling is not necessarily a bad thing. Individuals who gain weight subsequently 'reset' their body weight, therefore, over a longer time period resulting in stability of weight. Whilst all individuals will to some extent weight cycle, it is hypothesised that the size and number of fluctuations in weight and the level of consciousness of weight change, may be problematic in terms of diminished motivation and compliance with each subsequent cycle (Brownell and Rodin, 1994). The available evidence does not appear to support this hypothesis finding no difference in the ability of individuals to lose weight over cycles although it is acknowledged that the evidence is weak (Brownell and Rodin, 1994).

Attrition

The importance of retaining participants across weight loss programmes has been alluded to throughout discussions. Indeed the NICE guidance (NICE, 2014), alongside specified weight loss outcomes, recommends that 60% of participants of behavioural weight management programmes complete the programme. The importance of attrition is discussed below as an introduction to research presented in this thesis.

Public sector organisations responsible for managing obesity are increasingly commissioning commercial sector organisations in an attempt to provide large scale weight management support. Weight Watchers and Slimming World both have multiple contracts with various public sector organisations (Weight Watchers, 2009 and Slimming World, 2016). Both organisations have over 40 years of experience providing weight management services, building their business on the ability to attract and retain customers and published evaluations often shed a positive light on this commercial sector provision (Heshka et al., 2000, Heshka et al., 2003, Truby et al., 2006 and Stubbs et al., 2011). Despite this, even these organisations struggle with attrition. Two large scale evaluations, of "Weight Watchers on Prescription" (n=29,326) and "Slimming on Referral" (n=34,271), both report completion rates (individuals attending ≥10 of 12 session) of just 58%.

This level of attrition is, however, favourable to the level of attrition reported in peer reviewed studies of attrition. Table 1.9 presents the literature summary table from Moroshko, Brennan and O'Brien (2011). It has been adapted and expanded to include further relevant research, specifically research published post-2011. This literature search was limited to non-surgical, non-pharmacological weight loss programmes. Programmes aimed at children and post-partum women were also excluded. Weighted by the sample size reported in the studies, the average attrition rate for the identified studies is just 40%.

Further, drop-out from, and non-adherence to, treatment is observed in many related areas of healthcare. Hanson et al. (2013), for example, report similar attrition rates from an exercise-on-referral programme (53.5% of individuals engaged at week 12) and, in their systematic review, Belita and Souraya (2015) report attrition rates ranging between 10.8% and 77.0% from smoking cessation programmes. Further, in a meta-analysis of pharmacological treatments for obesity, Rucker et al. (2007) report attrition rates of 30% and 40% (for the drugs orlistat and sibutramine and rimonabant respectively).

Previous systematic reviews (Moroshko, Brennan and O'Brien, 2011) have found no evidence of robust predictors of attrition. More promising research has focused on social and behavioural reasons for drop-out although little research in this area exists. Moroshko, Brennan and O'Brian (2011) highlight "the need to focus on theoretically grounded psychological and behavioural predictors of dropout".

	Sample					Analysis			
Reference	N=	Male (%)	Age (mean)	BMI (mean)	Country	Definition of attrition	Methods	Length	Attrition
Ahnis et al., 2012	164	14	43	39.5	Germany	Attends at week 52	T-tests, χ^2 tests and logistic regression	52 weeks	43%
Bautista-Castano et al., 2004	1,018	23	38	31.7	Spain	Reaches target weight	Cox regression analysis	2 years	70%
Bennett and Jones, 1986	105	0	40	32.8	UK	Attends at week 16	T-tests, Mann-Whitney U tests and Fishers Exact Probability tests	16 weeks	30%
	62	0	39	32.9	UK	Attends at week 16	T-tests, Mann-Whitney U tests and Fishers Exact Probability tests	16 weeks	23%
	159	0	50	32.3	UK	Attends at week 16	T-tests, Mann-Whitney U tests and Fishers Exact Probability tests	16 weeks	57%
Bernier and Avard, 1986	62	0	44	-	Canada	Attends week 10	MANOVA	10 weeks	16%
	62	0	44	-	Canada	Attends week 16	MANOVA	10 weeks	25%
	62	0	44	-	Canada	Attends week 34	MANOVA	10 weeks	39%
Bradshaw et al., 2010	119	0	46	35.4	New Zealand	Attends ≥8 sessions	Logistic regression	10 weeks	42%
Brook et al., 2014	502	31	44	-	Australia	Attends first appointment	T-tests and χ^2 tests	-	35%
	392	30	47	49.4	Australia	Attends >50% of scheduled appointments	T-tests and χ^2 tests	-	28%
Brownell, Heckerman and Westlake, 1979	147	18	45		-	-	-	10 weeks	44%
Busetto et al., 2009	300	27	52	>25	Italy	Attendance >12 months	Cox regression analysis and Kaplan-Meier estimates of survival	3 years	75%
Carels et al., 2003	44	0	55	36.4	USA	Engagement at 6 months	Correlations and t-tests	6 months	16%
Chang, Brown and Nitzke, 2009	129	0	25	31.8	USA	Attends 6 month follow up	Forward stepwise multiple logistic regression	10 weeks	51%
	129	0	25	31.8	USA	Attends 12 month follow up	Forward stepwise multiple logistic regression	10 weeks	67%

Clark et al., 1995	39	-	47	32.6	USA	Attends ≥8 sessions	Discriminant function analysis and univariate f-tests.	12 weeks	49%
Clark et al., 1996	143	31	42	41.3	USA	Number of sessions attended	Correlation and multiple regression	26 sessions	19.5 sessions
Collins et al., 1983	68		41		Australia	-	-	15 weeks	24%
Colombo et al., 2014	98	37	45	35.2	Italy	Engagement at 1 month	Mann-Whitney's U tests and logistic regression	6 months	21%
	98	37	45	35.2	Italy	Engagement at 6 months	Mann-Whitney's U tests and logistic regression	6 months	57%
Compe, Papoz and Avignon, 2003	299	19	44	33.5	France	Engages with the programme	Logistic regression	6 months	68%
Cresci et al., 2013	331	27	43	38.8	Italy	Attendance to all four follow up sessions	Logistic regression	6 months	65%
De Panfilis et al. 2008	92	13	42	38.5	Italy	Attendance at 6 months	Logistic stepwise regression	6 months	33%
De Panfilis et al., 2007	68	12	39	36.1	Italy	-	-	8 months	22%
Douglas, Ford and Munro, 1981	132		37	-	Scotland	Attendance to ≥2 clinic visits	-	12 months	21%
	132		37		Scotland	Attendance ≥1 year	-	12 months	69%
Edmunds, Ntoumanis and Duda, 2007	49	16	45	38.8	UK	Engagement at 3 months	Multilevel regression analyses	3 months	49%
Ek et al., 1996	83	100	43	37.8	Sweden	Engagement at 2 years	ANOVA	3 months	31%
	24	33	45	39.8	Sweden	Engagement at 2 years	ANOVA	3 weeks	33%
	80	45	44	37.7	Sweden	Engagement at 2 years	ANOVA	6 weeks	43%
Elfhag and Rössner, 2010	247	29	41	41.4	Sweden	Attendance to five lectures	T-tests, χ^2 tests	5 weeks	36%
	157	-	-	-	Sweden	Unspecified engagement with programme	T-tests, χ^2 tests	4-5 months	42%
Fabricatore et al., 2009	224	20	44	37.8	USA	Completion of week 52 assessment visit	ANOVA, χ^2 tests and logistic regression	Various	17%
Feuerstein et al., 1989	122	0	38	31.4	USA	Average attendance	Descriptive	13 weeks	17%

Fontaine and Cheskin, 1997	109	35	44	42	USA	Number of weeks of participation	Correlation	Various	-
Fowler et al., 1985	129	5	20-60	>25	USA	Attends ≥7 sessions	Discriminate function analysis	10 weeks	43%
Graffagnino et al., 2006	418	-	50	38.0	USA	Weight measurement at 6 months	Correlation and t-tests	6 months	53%
Grave et al., 2005	1,785	12	44.6	38.2	Italy	Attendance at 12 month follow up	ANOVA, χ^2 test and logistic regression	12 months	52%
Greenberg et al., 2009	322	86	52	31	Israel	-	-	24 months	16%
Greenway, Bray and Marlin, 1999	184	-	-	-	USA	Attendance at week 8	χ^2 tests	-	10%
	186	-	-	-	USA	Attendance at week 8	χ^2 tests	12 weeks	13%
Gripeteg et al., 2010	267	34	40	43.1	Sweden	Completion of 12 weeks	Multivariate logistic regression	12 weeks	17%
Grossi et al., 2006	940	23	49	38.6	Italy	Undefined	t-test, Fisher exact test or χ^2 test	24 months	82%
Ortner- Hadžiabdić et al., 2014	124	26	48	41.6	Croatia	Attendance at month 1	Mann–Whitney U-test and λ^2 tests.	1 week	2%
	124	26	48	41.6	Croatia	Attendance at month 3	Mann–Whitney U-test and λ^2 tests.	1 week	10%
	124	26	48	41.6	Croatia	Attendance at month 6	Mann–Whitney U-test and λ^2 tests.	1 week	16%
	124	26	48	41.6	Croatia	Attendance at month 12	Mann–Whitney U-test and λ^2 tests.	1 week	32%
Hagen, Foreyt and Durham, 1976	42	0	-	-	USA	Attends ≥10 sessions	Duncan Multiple Range Test	12 sessions	38%
Harris et al., 1980	67	0	12-23	>25	USA	Attendance to final session	Correlation and ANOVA	12 months	53%
Hjordis and Gunnar, 1989	68				Sweden	-	-	48 months	18
Ho et al., 1995	156	-	41	33.1	USA	Drop out over 6 months	Cox proportional hazards survival analysis	6 months	9%
Honas et al., 2003	866	27	47	-	USA	Attendance week 16	Logistic regression	16 weeks	31%
Huisman et al., 2010	101	48	58	35.3	Netherlands	Record of weight 6 months	ANCOVA and MANCOVA and multiple logistical regression	6 months	39%
Inelmen et al., 2005	383	-	15-85	>25	Italy	12 month attendance	Two sample t-test, Mann–Whitney–Wilcoxon rank-sum test and χ^2 test followed by multiple logistic regression	12 months	78%
Keegan, Dewey and Lucas, 1987	105	31	43	>25	Canada	-	-	10 weeks	24%

Kolotkin and Moore, 1983	271			>25	USA	-	-	12 weeks	59%
Komulainen et al., 2011	82	28	49	35.0	Finland	Attends 6 month session	Logistic regression	18 months	24%
Koritzky et al., 2014	52	20	44	34.1	USA	Undefined	Logistic regression	16 weeks	35%
LaPorte, 1992	94	30	>21	>25	USA	Attends all ten sessions	χ^2 test	10 weeks	28%
Lent et al., 2013	178	25	51	36.1	USA	Unspecified	Correlations, Fisher's exact and t-tests	5 months	13%
Leon and Rosenthal, 1984	47	9	42		USA			12 weeks	53
Marcus, Wing and Hopkins, 1988	66	0	39	>25	USA	≥6 or more sessions	T-tests	10 sessions	18%
Mavis and Stoffelmayr, 1994	101	14	42	-	USA	Attends session 10	χ^2 test	10 Sessions (14 weeks)	24%
Melin et al., 2006	117	17	50	39	Sweden	Attendance at 24 months	-	24 months	53%
Michelini et al., 2014	146	25	45	32.3	Italy	Engagement at 6 months	Odds Ratio (OR) and multivariate analysis	24 months	30%
Minniti et al.,2007	129	0	18-65	>25	Italy	Engagement at 6 months			37%
Mitchell and Stuart, 1984	414	0	38	>25	USA	Attendance at week 12	T-tests	12 weeks	24%
O'Leary, 2012	79	-	31-65	≥27	USA	Attendance at week 40	Logistic regression	40 weeks	37%
Packianathan et al., 2005	150	0	49	36.5	UK	Engagement at week 16	Ordinal logistic regression and Cox survival analysis	16 weeks	24
Pekarik et al., 1984	52	50	44	-	USA	≥8 or more sessions	T-tests	12 weeks	46
Prochaska et al., 1992	156	9	40	>25	USA	-	ANOVA	14 sessions, 10 weeks	-
Seaton and Rose, 1965	1,000				Scotland	Attendance after first meeting	-		24%
Sherwood, Jeffery and Wing, 1999	444	0	40	-	USA	Attends at 6 months	χ^2 tests	18 months	22%
	444	0	40	>25	USA	Attends at 18 months	χ^2 tests	18 months	15%
Sitton and Miller, 1991	209	17	38		USA	Engagement at 6 months	-	6 months	
Teixeira et al., 2004	158	0	48	31	USA	Attendance at week 16	Correlation and ANCOVA	16 weeks	14%

Teixeira et al., 2004	158	0	48	31	USA	Follow up at 16 months	Correlation and ANCOVA	16 weeks	30%
Trief et al., 2014	257	25	52	39.3	USA	Attends ≥9 sessions	Univariate analysis	16 core sessions	51%
Tseng et al., 2002	189	12	41	31.1	USA	Starts stage 2	Descriptive	4 weeks	6%
	189	12	41	31.1	USA	≥70% of sessions attended	Descriptive	12 weeks	39%
Yackobovitch et al., 2014	587	10	46	31.9	Israel	Attends week 10	Logistic regression	10 weeks	31%
Yass-Reed, Barry and Dacey, 1993	180	14	40	>29	USA	"Graduates" at week 26	Multiple discriminant function analysis	26 weeks	39

Table 1.9: Literature Summary of Weight Management Programmes and Attrition Rates.[7]

[7] Adapted from Moroshko, Brennan and O'Brien (2011).

1.7.5 What are the Strengths and Limitations of Behavioural Weight Management Programmes?

Thus far this section has provided broad discussions of behavioural weight management programmes such as the example evaluated in this thesis. The following syntheses discussions presented by summarising the strengths and limitations of behavioural weight management programmes.

Strengths of behavioural weight management programmes

- An ability to achieve evidence based outcomes in the short term (5% of greater reduction in initial body weight) as evidenced by robust controlled trial studies.
- The approach is scalable as evidenced by the significant number of individuals accessing such services each week and the proliferation of commissioned services within the health sector.
- The approach is affordable and using economic modelling has been shown to be cost effectives when as little as 1kg can be lost and sustained for £100 per patient.
- Several specific behaviour change techniques have been identified as being effective allowing for the beginning of theoretically evidenced approaches.
- Within discussion regarding the complex system of obesity the significant role of behavioural weight management programmes to build capacity and influence other factors within the system was acknowledged.

Limitations of behavioural weight management programmes

- There is a lack of long-term weight outcomes resulting in the reliance of potentially naive assumptions to assess cost-effectiveness.

- There is a lack of research which directly compares differing behavioural weight management programme approaches and therefore little is known about effective intervention design, intensity and duration.
- There is a lack of research on unintended consequences such as weight stigmatisation and effects of weight cycling.
- There is a lack of evidence regarding the effectiveness of intervention on sub-groups within the population.
- These interventions represent only a small part of a complex system and, thus, must be viewed as one component of a broader approach to obesity.

1.8 Aims, Objectives and Research Question

Aims and Objectives

The aim of this thesis is to understand factors associated with weight status, weight loss and attrition. To this effect the thesis is divided into four distinct chapters. Figure 1.13 outlines the overall structure of this thesis outlining the broad aims and objectives of the distinct pieces of research.

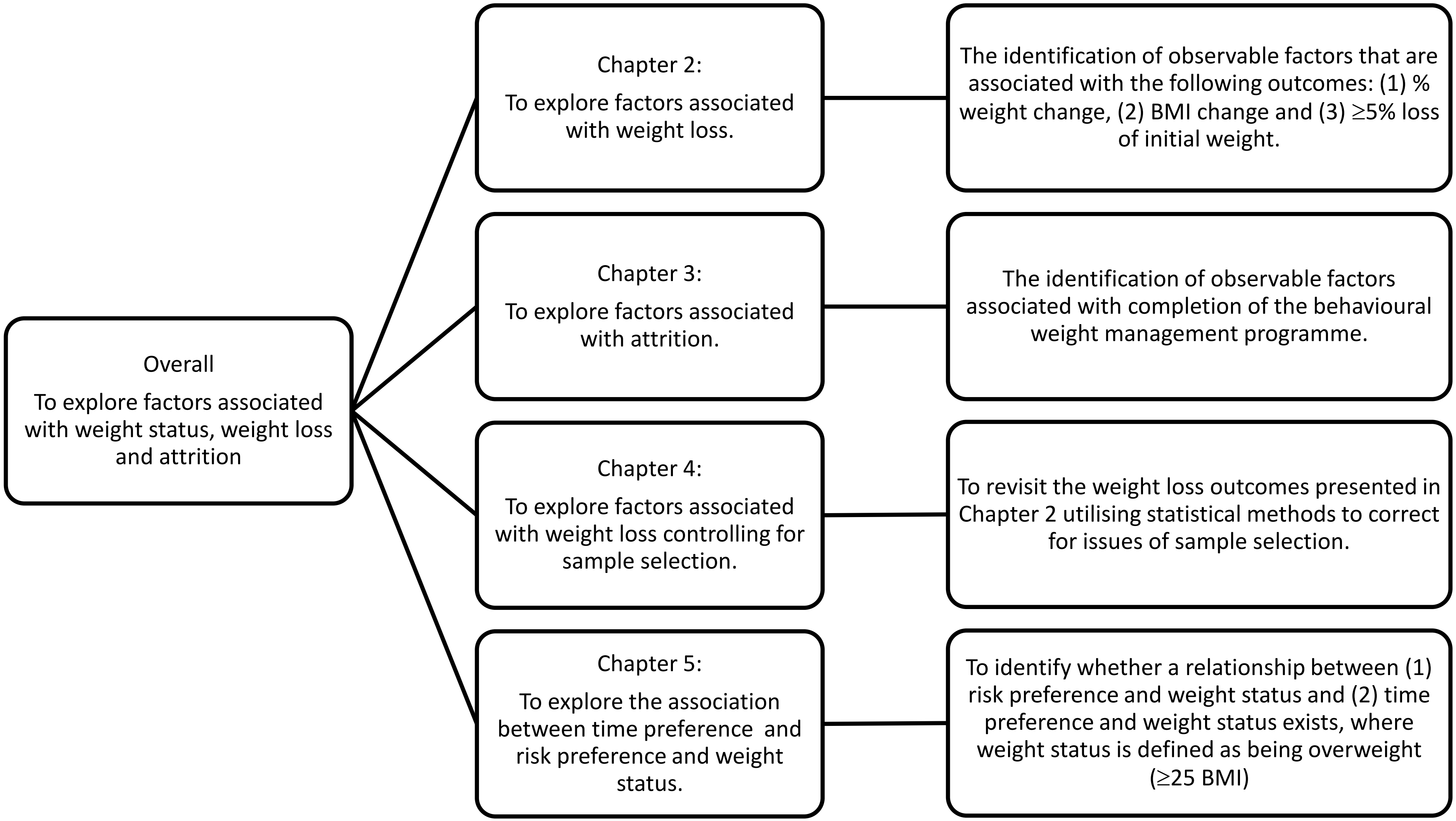

Figure 1.13: Aims and Objectives of the Research Presented in this Thesis

Research Questions

The thesis is structured around four main research chapters and a final discussion chapter. The discussions contained in the four research chapters are focused on specific primary and secondary research questions which are outlined below. The final discussion chapter, however, draws together the findings and conclusions and of the research chapters. It then guides the reader back to the concepts presented in Chapter 1, discussing the broader implications of the research as a whole. Chapter 6 ends with a discussion of the strengths and weaknesses of the research and opportunities for further research in this area.

Chapter 2

Primary Research Question

– What observable factors predict weight loss in a behavioural weight management programme?

Secondary Research Questions

– Do our findings reflect previous research?

Chapter 3

Primary Research Question

– What observable factors predict attrition in a behavioural weight management programme?

Secondary Research Questions

– Do our findings reflect previous research?

Chapter 4

Primary Research Question

- What observable factors predict weight loss in a behavioural weight management programme when controlling for sample selection?

Secondary Research Questions

- How do our findings compare to the methodological approach taken in Chapter 2?

Chapter 5

Primary Research Questions

- Is there an association between time preference and being overweight?
- Is there an association between risk preference and being overweight?

Secondary Research Questions

- Do our findings reflect previous research?

Chapter 6

Primary Research Questions

- What is the relationship between the findings of the 4 research chapters?
- What does this research add to existing knowledge?
- What does this research add to our knowledge of the effectiveness and cost effectiveness of behavioural weight management programmes?
- How does this research contribute to complex systems thinking of obesity
- What are the implications of this research on health inequalities research?
- What are the implications of this research on practice?

– What are the implications of this research on policy?

– What are the strengths and limitations of the research?

– What are the recommendations for further research?

Chapter 2

Factors associated with weight loss: Evidence from a publically funded weight management programme

2.1: Justification for the research

The ultimate objective of research exploring predictors of weight loss is to provide evidence to support the continuous development of effective weight management programmes. The identification of variables associated with inadequate weight outcomes will enable policy makers to target certain individuals or groups of individuals who are at risk of a lower probability of weight loss success. Targeting these individuals may include, for example, the provision of extra support, programmes tailored to their differing needs or the provision of incentives (financial or otherwise). This requirement to understand the variables associated with the probability of weight loss success and to provide more specialised provision for those less likely to succeed is recognised by Teixeria et al. (2005);

"*Identifying significant predictors of weight loss outcomes is central to improving treatments for obesity, as it could help professionals focus efforts on those most likely to benefit, suggest supplementary or alternative treatments for those less likely to succeed, and help in matching individuals to different treatments*."

Whilst the objective and value of the research is clear, current literature exploring predictors of weight loss is limited and, thus, insufficient to inform practical developments of treatment programmes. High quality research is therefore needed if the continuous improvement of treatment programmes is to be achieved (Stubbs et al., 2011).

Teixeria et al. (2005) published a comprehensive review of literature exploring psychosocial pre-treatment predictors of weight loss. The literature summary table presented by Teixeria et al. (2005) has been adapted and expanded here to include further relevant research, specifically research published post-2005 and/or exploring factors beyond the psychosocial variables of interest in the original review. Excluded from this search were studies of surgical, paediatric, post-partum and pharmacological weight loss interventions. In total 49 studies were identified and included, the results of this exercise are presented later in Table 1.6.

In their review, Stubbs et al. (2011) highlight the key limitations of the existing research as (1) generalisability of findings; (2) sample selection and size; (3) heterogeneity of evaluation methods; and (4) insufficient statistical modelling often as a result of retrospective evaluative practices. We contribute to the literature by analysing data from a weight management programme that address many of the concerns raised by Stubbs et al. (2011). The following discussions provide details of the key strengths of our research both in comparison to past literature and in its ability to meet the requirements of recommended advances in this area.

Early research of predictors of weight loss tended to be explored through trials conducted in university or clinical settings (Brownell and Rodin, 1994). Whilst of interest, Stubbs et al. (2011) questions the generalisability of such studies given the selective nature of the samples. Important psychological and behavioural differences between individuals selected for clinical interventions and the general population, significantly reduce the applicability of findings to wider weight loss settings. Further, because it is estimated that 95% of individuals attempting to lose weight will do so outside of a clinical setting (Stubbs et al., 2011), research which is more representative of the predominant weight loss methods (self–help and commercial programmes) is of high value.

We provide an evaluation of a publicly funded, commercial weight management service. The service reduces weight through dietary alterations and behaviour change, consisting of weekly group sessions over a period of twelve weeks with longer term monitoring. Whilst the specific commercial provider of the service is one of the most commonly accessed weight loss programmes in the UK, the 12 week intervention structure and content is also highly reflective of interventions commissioned globally for the treatment of obesity (see Table 1.6). A significant strength of this analysis is, therefore, the high applicability of findings to existing and future service delivery.

Table 1.6 provides a summary of the main findings from the current literature regarding predictors of weight loss. Whilst some variables seem to display some predictive power much of the literature is inconsistent and inconclusive. One potential explanation for this inconsistency is the insufficient statistical power of some studies caused by small sample sizes, resulting in unreliable findings (Stubbs et al., 2011). Whilst research on weight change benefit from huge sample sizes[8] (Finucane et al., 2011), only a handful of studies exploring predictors of weight change achieve sample sizes greater than two hundred (see Table 1.6).

In contrast, our sample recorded data from 2,892 individuals who commenced the weight management programme.

[8] Finucane et al. (2011) estimates trends and their uncertainties of mean BMI for adults 20 years and older in 199 countries and territories. They obtained data from published and unpublished health examination surveys and epidemiological studies (960 country level data points elicited from a total combined sample of 9·1 million participants).

Allison and Engel (1995) recommend further research must take a planned and deliberate approach to the exploration of the predictors of weight loss rather than a retrospective evaluation of existing data. Analysis of variables based on theoretical underpinnings rather than availability are far more likely to provide valuable insights into correlates of weight loss (Stubbs et al., 2011).

The weight management service discussed in this thesis was commissioned in 2011. Prior to the commissioning of the service a complete evaluative plan was developed outlining purposeful and considered variables of interest, measurement methods and data collection processes. A comprehensive description of the weight management programme is presented in section 2.3 and Appendices 2 to 13. As a result of this planning activity, we contribute to the existing literature through the analysis of a rich dataset containing numerous variables of both academic and practical interest and an appropriate and robust approach to the statistical modelling and analysis of variables.

A further constraint to the achievement of reliable predictors of weight loss is the heterogeneity of evaluations. Inconsistent approaches to the elicitation of both predictor and outcome variables, the highly differentiated treatment approaches and analysis of potentially biased samples selected by researchers have resulted in difficulties in the comparability of studies and in drawing robust conclusions suitable for practical advancements in treatment. Stubbs et al. (2011) recommends future research should look to utilise standardised definitions of constructs, predictors and success.

Due to the planned approach of the evaluation, efforts have been made to measure variables and analyse and report outcomes supportive of comparison to past literature whilst not restricting the evaluation to sub-standard procedures. Multiple outcomes variables are explored allowing for a comparison to past studies including possible explanation of inconsistencies in findings. Further, great care was taken to ensure the use of robust and validated measurement methodologies to ensure the maximum value can be gained from the evaluation.

2.2: Introduction

UK based research exploring weight status suggests that obesity status is negatively associated with income in women (i.e. as income rises the prevalence of obesity falls) (NOO, 2014), is related to occupational status in men (higher professional occupations are associated with lower prevalence of obesity) and is negatively associated with education in both genders (i.e. higher education is association with lower prevalence of obesity) (Health and Social Care Information Centre (HSCIC), 2014). Further, research exploring health behaviours and obesity status suggests positive associations with ex-smokers, self-reported unhealthy eating, physical inactivity and hypertension in both genders and moderate alcohol consumption in women (HSCIC , 2014). The resulting policy implication of this evidence has been the development of programmes targeting these identified groups of individuals with the objective to reduce prevalence based health inequalities. Wang et al. (2006), for example, evaluates the success of a programme targeting urban, low socioeconomic status, black adolescents. It is reasonable to hypothesise that variables associated with higher weight status may also be associated with lower propensity to lose weight, however, this cannot be assumed.

Limited evidence is available exploring factors associated with weight change and in particular, propensity to lose weight. Table 2.1 has been adapted from Teixeria et al. (2005) and Stubbs et al. (2011) and presents the predictors of weight loss previously explored and the associations observed. This further highlights the inconsistencies in past research with many variables presenting mixed or merely suggestive relationships.

Variable	Relationship
Socio-Demographic	
Male	Positive
Age	Mixed
Ethnicity	Mixed
Marital Status	Mixed
Education	None
Weight factors	
Initial body weight or BMI	Positive
Early weight loss	Positive
Adipocyte hyperplasia	Positive
Weight cycling	Mixed
Body fat distribution / Total fat / Body composition	Mixed
Aspects of the service	
Attendance	Positive
Length of treatment	Positive
Self-monitoring	Positive
Goal-setting	Positive
Realistic weight loss goals and expectations	Mixed
Health behaviours	
Physical activity	Positive
Slowing rate of eating	Positive
Previous dieting (or weight loss) attempts	Negative
Exercise self-efficacy	Suggestive (+)
Perceived barriers to exercise	Suggestive (-)
Bulimic behaviour	Suggestive (-)
Dietary restraint	Mixed
Eating self-efficacy	Mixed
Binge eating	Mixed
Alcohol consumption	None
Emotional eating	None

Eating Inhibition	None
External eating	None
Cognitive (eating) restraint / Chronic dieting	None
Perceived hunger	None
Exercise social support	None
Mental health	
Perceived stress	Negative
Depression / Anxiety	None
Personality	
Personality	Mixed
Psychopathology	Mixed
Mood	None
Undefined	
Self-efficacy	Positive
Autonomy	Positive
Social support	Positive
Quality of life (obesity-specific)	Suggestive (+)
Body image / Body size satisfaction	Mixed
Self-esteem	Mixed
Internal locus of control	Mixed
Perceived social support	None
Cognitive performance	None
General cognitive style	None
Quality of life (general)	None

Table 2.1: Factors associated with weight change: A summary of the existing evidence [9]

As well as contributing evidence to existing hypotheses, new hypotheses are presented. Unexplored variables included in this analysis are; the presence of children, consistency of attendance to the weight management programme, referral type (self vs. professional

[9] Adapted from Teixeria et al. (2005) and Stubbs et al. (2011).

referral), time to treatment, smoking and physical health conditions (diabetes, CVD, mobility, hypertension) and a measure of individual's perception of their local area. Each of these new variables is discussed in the context of the COM-B theoretical framework for understanding behaviour (Michie, van Stralen and West, 2011). The COM-B theoretical framework proposes that behaviour is a product of one's capability, opportunity and motivation. The framework was derived from the identification of thirty-three psychological theories from which eighty-four theoretical constructs were identified. These were subsequently grouped into fourteen theoretical domains which map to the six constructs of behaviour that make up COM-B (Michie, van Stralen and West, 2011) (See Figure 2.1). These six constructs and a short definition of each are provided below.

1. Physical Capability: Physical skills, strength or stamina
2. Psychological Capability: Knowledge, psychological skills, such as planning, attention, strength and stamina, to engage in the necessary mental processes such as, interpersonal skills, memory, attention, decision processes.
3. Physical Opportunity: Opportunity afforded by the environment involving time, resources, locations, cues.
4. Social Opportunity: Opportunity afforded by the social environment, social cues and cultural norms, social acceptability and expectations.
5. Reflective Motivation: Active thought processes – attitudes and beliefs about what is good or bad, the costs and benefits of doing something, beliefs about consequences, goals, plans, and intentions.

6. Automatic Motivation: Less conscious thoughts processes that drive behaviour - emotional reactions, desires (wants and needs), impulses, drive states, habits, reinforcement, associative learning and reflex responses.

(Michie, van Stralen and West, 2011)

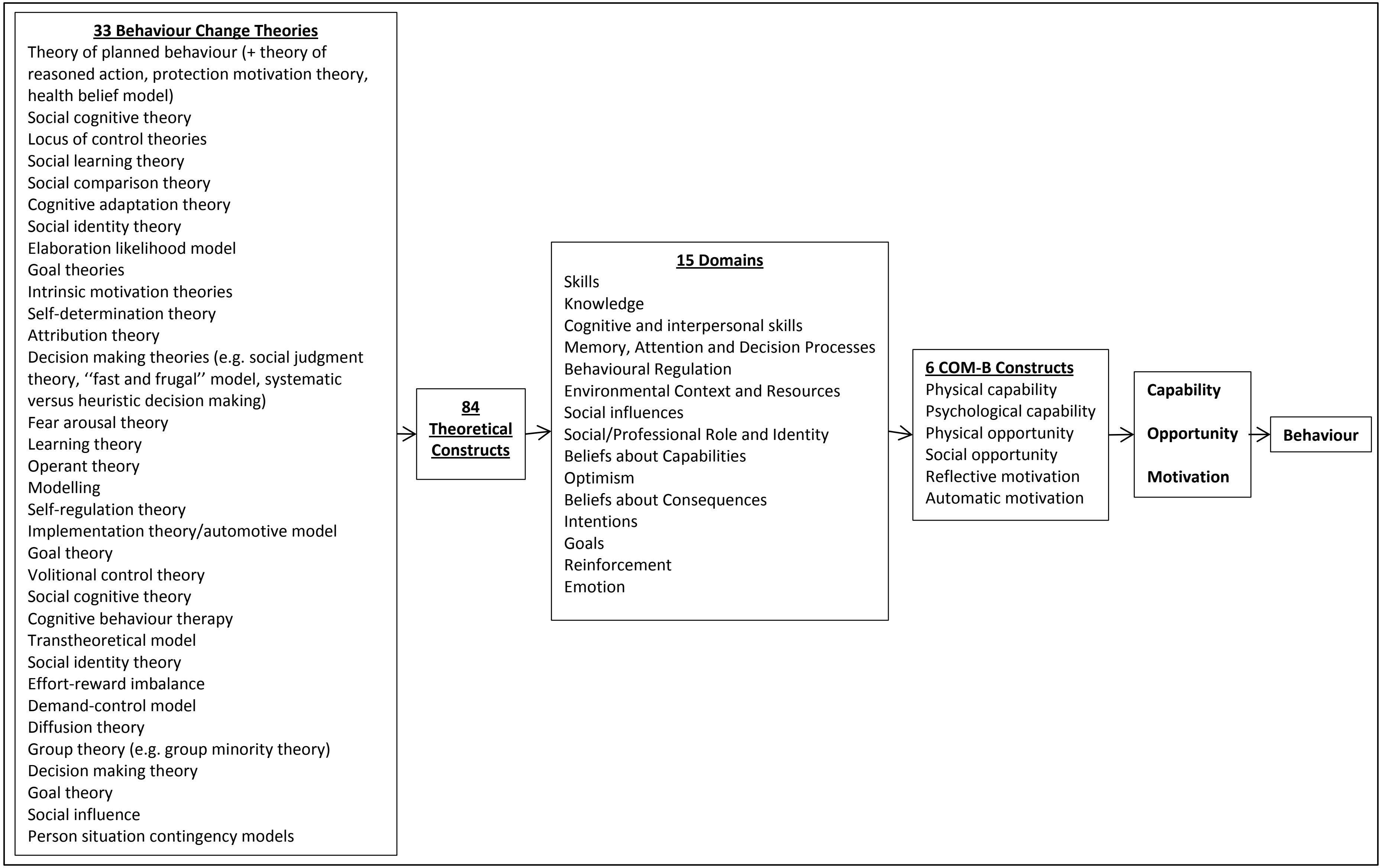

Figure 2.1: Theories, domains and constructs of the COM-B Theoretical Framework (adapted from Michie, van Stralen)

The framework has been chosen for the basis of discussions for a number of reasons outlined below.

1. The framework is specifically designed to understand the theoretical drivers of behaviour. The outcomes of weight loss and attrition studied in our research are fundamentally a product of behaviour change whether this is conscious and deliberate or unconscious and automatic, driven by psychological, sociological, environmental or other drivers of behaviour.
2. The integrative nature of the framework provides a comprehensive approach to understanding the theoretical relationship between variables.
3. The framework, in comparison to individual psychological or other integrated models, reflects wider non-cognitive-psychological drivers of behaviour due to the multi-disciplinary approach utilised to the construction of the framework.

Due to the complexity associated with the causes of weight loss and attrition, it is appropriate that a comprehensive, integrative, cross-disciplinary, behavioural framework is applied. Whilst the framework is not exhaustive in the behaviour change theory utilised, it does provide reference to behaviour change theories beyond cognitive-psychology such as 'heuristic decision making' found within the field of behavioural economics and a number of constructs which result in the inclusion of an independent domain for the influence of environmental context and resources (see Figure 2.1).

The framework also allows for the identification of the individual theory or theories from which the constructs were derived. This allows for a more thorough exploration of the theoretical relationships between the variable and overcomes some of the limitations of the framework which are outlined below:

1. The approach breaks down the identified theories of behaviour change into individual constructs and rebuilds these constructs into the integrative framework presented above. It is argued that the overall connotations and intricacies of the individual theories upon which it is built are somewhat lost in this approach resulting in a misunderstanding of the construct's original definitions.
2. The non-cognitive-psychological constructs are not comprehensive or irreducible. Behavioural economic concepts such as those outlined by DellaVigna (2009)[10] or a thorough account of the wider system factors outlined in the Foresight Whole Systems Map (see Figure 1.1) are only broadly presented within the framework and lack specificity.

The following discussions, therefore, present the relationship between the new variables and weight loss outcomes in the context of the COM-B framework but also against concepts prevalent within the field of behavioural economics and reflecting on previous discussion of complex systems utilising the Foresight Map (see Figure 1.1).

Children

Within the Foresight Whole System Map for obesity (See Figure 1.1) there are two factors which specifically relate to parental influence on children's diet and activity. Parental

[10] Nonstandard preferences, such as time preferences (self-control problems), risk preferences (reference dependence), and social preferences. Nonstandard beliefs such as overconfidence, the law of small numbers, and projection bias and nonstandard decision making such as framing, limited attention, menu effects, persuasion and social pressure, and emotions (DellaVigna, 2009)

influence is underpinned by the social opportunity component of the COM-B model and, specifically, theoretical constructs of social norms (i.e. “socially determined consensual standards that indicate what behaviours are considered typical and/or proper in a given context” (Cane, O’Connor and Michie, 2012)) and social support (i.e. the apperception or provision of assistance or comfort from any interpersonal relationship in an individual's social network, typically in order to help them cope with a variety of biological, psychological and social stressors (Cane, O’Connor and Michie, 2012). This parental relationship is found empirically by McLean et al. (2003), for example, who find strong evidence that higher involvement from parents increases the probability of successful weight loss in children. Although not reflected in the Foresight Map, the hypothesis that the reverse relationship exists (i.e. the effect of children on parental weight loss) is presented here.

Firstly, we present the theoretical argument for the positive influence of the presence of children on weight loss. With a political focus on childhood obesity (see Chapter 1) one may hypothesise that, in comparison to adults without children, adults with children have perhaps a higher probability of exposure to factors promoting healthy eating and physical activity (e.g. governmental social marketing efforts and school food standards) and decreased exposure to factors which lead to over-consumption (e.g. the restriction of takeaway outlets in proximity to schools). The hypothesised consequences of this exposure to differing factors between adults with and without children are presented on the following page.

1. Increased reflective motivation for behaviour change.

Increased exposure to factors such as social marketing and school food standards may encourage a higher degree of reflective motivation about weight status and diet. Reflective motivation includes deliberate thought regarding the costs and benefits of behaviour, thus, theoretically, exposure to such factors should both encourage these reflective thought processes and, by promoting the benefits of achieving a healthy weight, influence behavioural decisions towards behaviours aligned with the attainment of a healthy weight. Many of the traditional models of behaviour change which feed into COM-B include a reflective motivation element. The perceived benefit as a moderating factor on behaviour, for example, is a specified construct within the Health Belief Model (Janz and Becker, 1984). Influence individual's reflective process, to an extent, relies on assumption of rationality introduced in the previous chapter. Traditional behaviour change theories have relied heavily on the assumption that intentions engender behaviour change, however, Webb and Sheeran (2006), amongst others; provide clear evidence that, this is not the case. Whilst adults with children may, therefore, have a higher probability of exposure to such factors the empirical evidence to support the theoretical relationship is weak.

2. Increased physical opportunity for behaviour change.

Decreased exposure to factors, such as the restriction of take-away outlets in proximity to schools and the restriction of advertising around children's television programmes, reduces the physical opportunities for adults with children to overconsume. Within the COM-B framework, physical opportunity refers to the opportunities afforded by the environment for engagement in behaviour. Exploring the individual models of behaviour, the influence of the environment is one of three constructs within Social Cognitive Theory (Bandura, 1986).

It should be noted, however, that within Social Cognitive Theory the environment is referred to in a broad sense, encompassing the socio-cultural also (Bandura, 1986). The physical opportunity construct of the COM-B framework also refers to the cues in the environment which trigger behaviour. This 'cue to action' is prominent within the Health Belief Model (Janz and Becker, 1984), however, within this model this construct refers to cues in the broader sense i.e. that a cue can be also be internal (e.g. physiological and psychological) (Janz and Becker, 1984). Empirically this theorised relationship between physical opportunities and weight status has greater support with strong evidence for the effects of availability and marketing of unhealthy food (PHE, 2014). Given, however, that policies reducing physical opportunities have focused on children, there is still a question of whether there is a secondary effect on parents compared to adults without children.

3. *Increase social opportunity for behaviour change*

Increasing children's exposure to healthy eating and physical activity factors may also increase the probability of parental engagement in healthy behaviour through a social mechanism. Within the COM-B framework social opportunity refers to opportunity afforded by the social environments such as social cues and cultural norms, social acceptability and expectations. The hypothesis is that if policies are successful children's preferences will shift to healthier behaviours and, thus, in turn influence the behaviours of parents due to the strong and influential social bond that exists between parent and child. Within individual theories subjective norms (i.e. an individual's perception about a behaviour, which is influenced by the judgment of significant others) is a significant construct of the Theory of Planned Behaviour (Ajzen, 1985) whilst, as previously mentioned, the influence of the social environment is also referred to within Social Cognitive Theory. The available empirical evidence supports the theorised influential nature of children on parental food purchasing behaviour, however, the type of purchases include both healthy and unhealthy food choices (for example, Turner, Kelly and McKenna, 2006; Wingert et al., 2014 and Gram, 2015).

Beyond the COM-B framework, is the contribution of behavioural economics to the proposed hypothesis in the form of the influence of children on parental risk preference. Whilst risk preference is not elicited in Chapters 2, 3 and 4, they are explored specifically in Chapter 5. The theoretical relationship between the presence of children and weight loss may to some extent, however, be explained by these concepts. In Chapter 5 we present the hypothesis that a relationship exists between risk aversion and weight status i.e. a lower BMI is related to higher risk aversion. Here we present the hypothesis that parenthood increases risk aversion which in turn is a mediating factor promoting weight loss. The relationship between parenthood and risk aversion is discussed by DeLeire and Levy (2004) who present the hypothesis that the presence of children provides an additional motivation to avoid ill-health (due to, for example, the financial pressures of dependents and/or a desire to increase years in good health) and, thus, are more likely to be risk averse. Indeed, Goerlitz and Tamm (2015) empirically test this theory utilising longitudinal data and show that parenthood leads to considerable changes in risk preferences over time. In both men and women risk aversion begins to increase as early as two years before parenthood, is largest following birth and disappears as a child becomes older (Goerlitz and Tamm, 2015).

We now present the theoretical argument for the negative influence of the presence of children on weight loss.

Above, we discuss how children affect food purchasing through a social mechanism and present an argument for the positive effect, however, we also acknowledge the body of evidence which present the negative social influence toward the purchasing of unhealthy food. There is clear evidence within the literature regarding children's influence on parental purchasing in general (McNeal, 1992, 1999; Acuff, 1997, Austin and Reed, 1999; Summerskill, 2001), however, of interest is the literature discussing food purchases. Stoltman et al. (1999), for example, finds evidence of both the higher influence of children regarding food purchases specifically and higher disagreement between parent and child preferences regarding food products. In general authors suggest this conflict results from a parental desire for healthier products in comparison to children's preferences for unhealthier items (Nichollsa and Cullen, 2004 and Stoltman et al., 1999). It is hypothesised, therefore, that these cues by children to purchase and consume unhealthy food may also influence the purchasing and consumption decision amongst parents. Specifically, it increases the physical opportunity for unhealthy consumption (e.g. through the presence of unhealthy foods within the home) and the social norm of unhealthy eating (e.g. I treated my child therefore I should treat myself). Whilst it is anticipated that policy will alter children's preferences, the realisation of this change will certainly require time and, therefore, the theorised negative social influence of children on parental weight loss is likely to persist.

Reflecting back to the COM-B framework, it is also hypothesised that the increased responsibilities associated with the presence of children may decrease an individual's psychological capability and physical opportunity to engage in healthy behaviours. Parenthood and, thus, the dependence of children inevitably results in increased cognitive load and decreased time and resource which may disable parents from engaging in the behaviours associated with weight loss.

In our research, number of children is collected as a continuous variable which is transformed into a binary variable where 0=no children and 1=presence of 1 or more children. The binary variable is in line with the presented hypotheses that it is the presence of children that influence weight loss. Arguably we may expect increasing effects with increasing number of children, however, this hypothesis is not, however, tested.

Consistent Attendance

A fair amount of literature exists exploring the relationship between frequency of attendance and weight loss outcomes (for example, Stubbs et al., 2011; Hollis et al., 2008; Sacks et al., 2009 and Karlsen, Søhagen and Hjelmasæth, 2013). This literature consistently reports a positive association between the frequency of attendance and weight loss. Research on frequency of attendance is of value; however, in our research we explore pattern of attendance. Specifically, we explore the binary variable of consistent attendance, where; consistent attendance indicates no periods of absence prior to drop out. Below we present two hypothesised relationships between consistency of attendance and weight loss outcomes.

1. *Increasing exposure to the service increases the probability of higher weight loss*.

This hypothesis is underpinned by three constructs of the COM-B framework. Specifically we hypothesise that increased exposure to the weight management service increases social opportunity, psychological capabilities and reflective motivation. This hypothesis reflects discussions presented in Chapter 1 regarding the differing exposure to factors outlined in the Foresight Obesity System Map and the effect this exposure has on weight. As previously discussed, exposure to the weight management service aims to alter factors found in the individual psychological and social psychology clusters within the Foresight Map which subsequently alter the relationship an individual has with factors in the food consumption and individual activity clusters resulting in a rebalance of the core loop within the map (see Figure 1.1). Each of the COM-B constructs underpinning the theorised relationship between consistent attendance and weight loss is discussed below.

The weight management service studied in this thesis is a group based service. As previously referred to, group based approaches have been found to be more cost effective and more effective in terms of weight loss. The theoretical foundation for this finding is the social opportunities afforded by group delivery of weight management. Specifically individuals who consistently attend the service receive a higher exposure to social comparisons, social norms and social support. Turning to individual psychological theories, Social Comparison Theory (Festinger, 1954) suggests that individuals compare themselves to similar others on salient domains, which results in the desire to reduce perceived discrepancies (Festinger, 1954). Strictly, Social Comparison Theory is not a behaviour change theory as it focuses purely on cognition; however, it is of relevance to the weight management service studied in this thesis due to the formation of groups of similar others (i.e. from similar geographical areas, of similar weight status with similar behavioural goals) by which individuals are able to compare themselves on salient domains (i.e. weight loss). Where individual weight loss achievements are lesser than those of group, this theoretically leads to positive behaviour change. This concept is closely related the concept of social norms (a key construct within the Theory of Planned Behaviour (Ajzen, 1985) whereby ones behaviour is governed by their perception of the behavioural expectation of the group. Within the weight management service higher exposure through consistent attendance is hypothesised to be related to an increased perception of successful weight loss as the social norm. Finally, increase exposure to the group provides increased received social support which has been discussed previously.

Consistent attendance further increases the probability of success through increased psychological capabilities, specifically, increased skills and knowledge. As discussed in Chapter 1, a key aim of the weight management service is to increase the capacity of individuals to match the complexity of the environment they face.

Finally, increasing exposure to the weight management service should also increase an individual's reflective motivation through increased exposure to weight loss goals and reinforcement of intentions and beliefs. The importance of reflective motivation (i.e. the deliberate contemplation regarding the costs and benefits of behaviour) is discussed previously.

Reflecting on the behavioural economic literature consistent attendance may also be underpinned by theories of limited attention (DellaVigna, 2009) and availability heuristic (Tversky and Kahneman, 1975). The strictest form of the standard economic model assumes that individual's make decisions using all the information available to them. This assumption has, from early on, been challenged and economic models whereby individual's simplify complex decision by using only a subset of information have been developed and utilised

(Simon, 1955). This use of a subset of information is described within theories of limited attention (DellaVigna, 2009). Further, the availability heuristic offers theoretical reasoning for what limited information may be taken into consideration during decision making processes. The availability heuristic refers to the likelihood of behaviour change resulting from how easily prior information comes to mind (Tversky and Kahneman, 1975). The availability heuristic often refers to the effect of recent and salient events on behaviours whereby individuals utilise information from these event whilst disregarding other relevant factors (Kahneman, 2011). The importance, therefore, on consistent attendance on weight loss is the ensure the continued salience and availability of weight loss promoting factors which influence consumption and physical activity decision making processes.

2. *Both attendance and weight loss are a product of a third unobservable factor; pre-existing motivation*.

This hypothesis proposes that low motivation at the initial stage of the programme may continue throughout the service resulting in both inconsistent attendance and poor weight loss outcomes. Theoretically this is underpinned by the supposition that the extent of one's reflective motivation (such as individual goals, intentions and beliefs) is present prior to initiation and remains unchanged throughout the service, thus, affecting both attendance and weight loss behaviours. Intentions and beliefs are prominent in a number of behaviour change theories, including the Theory of Planned Behaviour (Bandura, 1986), where behaviour is partly driven by one's attitude towards the outcome (i.e. one's belief that weight loss is beneficial). If belief in the value of weight loss is relatively low this may subsequently reduce the probability of consistent attendance and weight loss specifically.

The choice to utilise measures of attendance consistency rather than frequency of attendance is subtle but has important implications for the continuous improvement of weight management services. Unlike frequency of attendance, the value of the exploration of the relationship between consistent attendance and weight loss is that if consistent attendance is indeed a predictor of successful weight loss it provides weight management services with the empirical evidence to use missed appointments as a trigger for tailored support to increase the probability of successful outcomes. Behaviour change techniques employed as a consequence of a missed appointment are likely to differ based on the theoretical association between consistent attendance and weight loss. Therefore, whilst theoretical reasoning's for the proposed hypotheses have been presented, the limitation of our research is that the theoretical underpinning will not be identifiable.

Finally, reflecting back to discussions in Chapter 1, a significant aim of the weight management service is that learned consumption and energy expending behaviours should become 'habits' i.e. that the behaviours are no longer conscious activities but are automatic and sustained (Lally, Chipperfield and Wardle, 2008). Under the assumption that the development of healthy habitual behaviours support weight loss, consistent attendance is hypothesised to be a significant predictor of successful weight loss as it demonstrates more habitual engagement in behaviours which are perceptually linked to weight loss behaviours compared to non-consistent attendance which evidences a more sporadic behavioural pattern.

Self-referral

At the referral stage of the weight management programme evaluated in this thesis the referring healthcare professional was asked to indicate the reason for the referral; (1) patient request, (2) health professional referral, (3) underlying health condition or (4) weight loss required for health intervention. The former three options were grouped to create the binary variable where 0=medical or healthcare professional referral and 1=self-referral. The COM-B framework provides theoretical arguments for both a positive and negative relationship between self-referral and weight loss outcomes. These two arguments are presented below.

1. *Self-referral and weight loss: A positive relationship*

The hypothesis presented here is that referral type may serve as a good proxy for pre-existing motivation for behaviour change i.e. individuals who self-refer evidences pre-existing higher motivation for behaviour change which over time results in more successful weight loss outcomes. The idea of a pre-existing motivation has been discussed previously. Of further interest when discussing the variable self-control is the theoretical argument as to why self-referral can be considered a proxy for existing motivation. Locus of Control Theory (Rotter, 1966) refers to the extent to which individuals perceive that they can control events which affect them. The theory proposes a scale whereby at the 'internal control' end individuals believe they control the consequences of their behaviour whilst at the 'external control' end they believe the consequence of behaviour are outside of their control. Locus of Control Theory contributes to the 'belief in capabilities' domain which aligns to the reflective motivation construct within the COM-B framework. An internal locus of control has been shown to correlate with self-regulatory abilities (Rotter, 1966) which are required for weight loss success. We argue here that self-referral evidences a higher internal locus of control compared to non-self-referred individuals and that an internal locus of control is comparable beneficial in weight loss attempts compared to external locus of control and, therefore, why the relationship between self-referral and successful weight loss is positive.

2. *Self-referral and weight loss: A negative relationship*

Individuals who do not self-refer are referred due to an identified medical need. Two theoretical constructs underpin this relationship. The first is that non-self-referred individuals may have an increased perception of risk and secondly, they may have an increased perception of social pressure.

Turning first to perception of risk, we present this hypothesis in the context of the Health Belief Model (Janz and Becker, 1984). Two constructs from the Health Belief Model provide the theoretical argument for the proposed relationship. These are perceived severity and perceived susceptibility of a condition. The Health Belief Model proposes that as perception of severity and susceptibility increase so, therefore, just the probability of behaviour change. One can, therefore, argue that individuals who are referred due to a medical requirement will indeed have an increased perception of risk and, thus, an increased probability of engagement in weight loss behaviours.

Turning secondly to non-self-referral creating a perception of social pressure for behaviour, within the COM-B framework, the 'social influence' domain aligns to the social opportunity construct. In this context, social influence refers to the behaviour change (i.e. weight loss) that occurs due to interpersonal processes (i.e. the influence of the health professional). We therefore propose that the presence of the interpersonal relationship increases the probability for behaviour change and, therefore, why non-self-referred individuals may exhibit more successful weight loss outcomes.

It is within the behavioural economic literature that the nuances of these interpersonal processes as drivers of behaviour can be drawn, specifically the notions of social preference, social pressure and reciprocity. As presented in Chapter 1 the standard economic model assumes unbounded selfishness i.e. that individuals are purely self-interested and utility is dependent only on own payoff (DellaVigna, 2009). Classic economic experiments, such as the dictator game (Forsythe et al., 1994) and gift exchange games (Fehr, Kirchsteiger, and Riedl, 1993) have challenged this assumption finding that individuals take into account the preferences of others when making decisions. In the current context the concept of social preferences proposes that an individual will include preferences of the health professional into behaviour change decisions. It is proposed that this occurs through the mechanisms of social pressure and/or reciprocity. Social pressure refers behaviour change resulting from an individual's perception of other's beliefs and, thus, a perceived pressure to conform (Cialdini and Goldstein, 2004). In the current context the referral made by a health professional acts a cue to the beliefs of the health professional regarding weight-related behaviour change and, thus, the referred individual perceives a social pressure to conform to this expectation. Reciprocity refers to behaviour change resulting as a response to the action of another individual (Fehr and Gächter, 2000). In the current context the referral made by a health professional is perceived by the individual as an act of support and, thus, the referred individual follows an inherent desire to reciprocate by engaging in weight loss behaviours. In summary, the behaviour change associated with successful weight loss resulting from the interpersonal relationship between an individual and health professional can be driven by social preference, whether this is social pressure or reciprocity, concepts prominent within behaviour economic thinking.

Time between stages of the programme

Time between stages of the programme takes the form of two variables. The first is the number of days between the being referred to the service and registering to attend. The second is the number of days between registering for the service and attending the first week.

It is hypothesised that individuals demonstrating a longer period of time between stages of the programme will experience less successful weight outcomes. Similar to the variable 'consistent attendance', we present two theories supporting this hypothesis:

1. A larger time period between stages of the programme causes a decreased probability of successful weight loss.
2. The variables related to time between stages of the programme and weight loss are both products of pre-existing motivation. Low motivation results in both an increased period of time to the start of treatment and also poor weight loss outcomes.

The theoretical underpinning for pre-existing motivation as an unobserved variable which affects both the independent and dependent variable has been previously discussed.

Discussions here will, therefore, focus on why increased time between stages may cause a lesser probability of weight loss success and will largely draw on theoretical discussions within behavioural economics literature.

Firstly, we present discussions regarding time inconsistent preferences. As presented in Chapter 1, unbounded willpower is an assumption of standard economic theory challenged by behaviour economic thinking. The standard economic model assumes an individual's discount rate between two time periods is independent of when utility is evaluated implying time consistency in decision making (DellaVigna, 2009). In the context of the current hypothesis the decision to participate in the weight-management (evidenced as a self-referral and registration) should be consistent with future engagement in weight management behaviours due to a consistency in preferences. Experiments presented in the behavioural economics literature (summarised by Loewenstein and Prelec, 1992 and Frederick, Loewenstein, and O'Donoghue, 2002) challenge this assumption suggesting that discounting rates may be hyperbolic (i.e. steeper in the immediacy compare to the longer-term future) capturing a preference for immediate gratification and a deviation from previously formed plans for behaviour change. The econometric model for discounting is presented in Chapter 5 alongside discussion of the elicitation of time preference in studies of BMI. In the current context, under the assumptions of hyperbolic discounting one can imagine that as an individual moves away from the immediate point of decision (i.e. referral or registration) the probability of behaviour change (i.e. weight loss) lessens due to temporal inconsistencies in preferences.

Linked to time preference is the aforementioned limited attention and availability heuristic. In the context of time between stages of the programme and weight loss it is hypothesised that increased periods of time between stages results in the reduced salience of weight loss behaviours and, therefore, the decreased probability of such factors being integrated in decision making processes.

Smoking

Within the Foresight map, contained within the social psychology cluster, are two factors related to smoking (1) social rejection of smoking and (2) smoking cessation. The relationship between the two factors is presented as the social rejection of smoking as a positive effect on smoking cessation. Smoking cessation, however, contributes to the factor regarding the tendency to graze (i.e. tendency to graze increases with smoking cessation) which, through the factor 'dietary habit', feeds into the central loop within the map concerned with energy balance (see Figure 1.1). It is indeed well documented that smoking cessation is related to weight gain (NHS, 2016 and Chou, Grossman and Saffer, 2004) explained partly by the exhibition of compensatory behaviours whereby individuals replace smoking behaviours with food consumption, thus, increasing the probability of weight gain and inhibiting the probability of weight loss. In this context a significant limitation of our research is an inability to separate non-smokers into individuals who have never smoked and individuals who are ex-smokers due to the theorised difference in consumption habits between these two groups resulting from differences in exposure to smoking behaviours.

A second hypothesis, however, is that both weight loss (achieved through restricted consumption) and smoking cessation (achieved through a restriction on smoking behaviour) are a consequence of self-control factors. Based on this hypothesis one would expect to see the clustering of unhealthy behaviours, such as smoking and less success weight change at an individual level. Self-control issues or temporal inconsistencies in preferences have been discussed previously.

Setting aside discussions of self-control, in the context of smoking and weight loss, one can argue that individual discount rates (i.e. that rate at which an individual discount future benefits) can effect smoking and weight loss decisions. The hypothesis is that individuals who heavily discounts future benefits may be more likely to engage in risky health behaviours such as smoking and less successful weight loss. This hypothesis relies, however, on the assumption that time preferences translate across multiple health behaviours. Empirically there is support for this hypothesis. Andersen and Mellor (2008), for example, find evidence that a number of risky health behaviours are influenced in a consistent manner by individual’s risk preferences, adding additional support to earlier research such as Viscusi and Hersch (2001), Hersch and Viscusi (1998) and Hakes and Viscusi (2007).

Physical Health

Within our research the presence of a number of health conditions are recorded by the healthcare professional. Within analyses we include five groups of conditions; (1) registered disability, (2) diabetes, (3) CVD, (4) mobility co-morbidities and (5) hypertension. It is hypothesised that the presence of a health condition increases the probability of successful weight loss outcomes.

Within the COM-B framework this hypothesis is theoretically underpinned by the reflective motivation construct whereby an individual's belief about the consequences of weight loss behaviour will differ with the presence of a health condition. Reflecting on specific psychological models, this theory is best reflected in the Health Belief Model (Janz and Becker, 1984) where presence of a health condition may increase the perceived severity of obesogenic behaviours and the perceived benefits of weight loss, thus, increasing probabilities of success.

Extending discussions beyond the COM-B framework to concepts found within the behavioural economics literature we turn attention to prospect theory (Kahneman and Tversky, 1979). Prospect theory is a descriptive theoretical reasoning for decisions made under risk and uncertainty (Kahneman, 2011). Of particular interest to current discussion is one of the fundamental principles of prospect theory; reference dependence. This principle proposes that individuals evaluate outcomes as deviations from a reference point (Brougham and John, 2007). A second principle of prospect theory is loss aversion whereby individual higher dislike for losses compared to the equivalent gain results in risk seeking behaviour over losses but risk averse behaviour over gain. In the current context it is argued that the presence of a health condition frames engagement in weight loss behaviour as a gain. An individual's current reference point is the presence of a health condition whilst engagement in weight loss behaviours is associated with alleviation of some of the systems of the health condition (i.e. a gain) and, therefore, decision of these individuals are more likely to be risk averse. The absence of a health condition frames weight loss behaviour as avoidance of a loss and, thus, in this case an individual may comparably more risk seeking. As is further discussed in Chapter 5 risk aversity is hypothesise to be positively correlated with engagement in health promoting behaviours as risk averse individuals are willing to commit more time and resource (in this context engagement in weight loss behaviours) to avoid the potential losses (i.e. ill-health) associated with obesity.

Perception of local area

The final variable discussed is 'perception of local area'. "Perception of local area" refers to an individual's perception of the opportunities within the immediate environment for engagement in healthy behaviours (such as the availability of healthy food and physical activity opportunities). The theoretical underpinning for the relationship between this variable and weight loss has been discussed at length in Chapter 1 in the context of complex systems thinking. Despite the clear theoretical influence nature of the external environment on healthy behaviours such as weight loss (Rössner (2008), little empirical evidence exists exploring correlations between environments and weight loss (Stubbs et al., 2011). We contribute to the current evidence through the analysis of perceptions of local environments on weight loss. A comprehensive description of variables is presented in Table 2.5 and discussions of findings in the context of past research are presented in Section 2.6.

Overview of the Chapter

This chapter explores factors associated with weight loss. It firsts provides an overview of the weight management programme analysed. Following this, six analyses are presented; three outcome variables at two time points. The three outcomes variables explored are significant weight loss (≥5% of baseline bodyweight), percentage weight change and BMI change. The two time points are engagement at week 10 of the service and attendance to week 12 of the service. Explanatory variables include socio-demographic, weight, aspects of the service, health behaviours, physical health, mental health and personality factors. Details of the variables and the approaches are discussed throughout this chapter.

2.3: Overview of the programme

2.3.1: Overview

The weight management programme[11] was developed in 2011 to fulfil an unmet need for lifestyle weight management support in County Durham and Darlington (see Appendices 2, 3 and 4).

Lifestyle weight management, also referred to as Tier 2 weight management, interventions refer to behaviour change programmes with the objective to reduce energy intake through diet modification and/or increase energy expenditure through physical activity. They are non-surgical, non-pharmacological approaches to weight loss. A graphical representation of the tiers of obesity treatment can be found in Appendix 3.

Three organisations worked together to deliver the weight management programme

1. The local authority (Durham County Council). Responsible for:
    a. Commissioning the weight management provider.
    b. Administration and management of the weight management programme.
2. Registered healthcare professionals (primarily GPs and practice nurses). Responsible for:
    a. Identification of individuals eligible for the programme.
    b. Referral to the programme.
3. The weight management provider (Slimming World). Responsible for:
    a. Delivering the 12 week service.

[11] The weight management *programme* refers to the full weight management journey from referral to six months self-reporting of weight. The weight management *service* refers to the specific 12 week weight management intervention.

From the perspective of an individual participating in the programme, there are three broad stages, as represented in Figure 2.2. Details of each stage are outlined below.

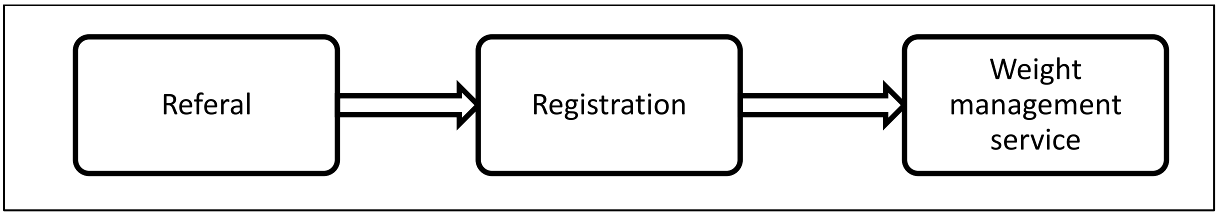

Figure 2.2: Structure of the weight management programme

2.3.2: Referral

Referrals were made for two main reasons; (1) the patient requested a referral or (2) a healthcare professional advised a referral. The referral was made by a healthcare professional by completing and sending an electronic referral form to the LA administration team. The referral form can be found in Appendix 4. A key role of the healthcare professional was to provide assurance regarding individual's suitability to participate in the service. Four exclusion criterions, based on an individual's health status, were established. Details of these can be found in Appendix 5. Guidance was provided to healthcare professionals to support effective referrals. This guidance is presented in Appendix 6.

Reducing inequalities is a predominant objective of most public health organisations. Reducing inequalities in opportunities and access to weight management was, therefore, a key objective outlined in the service specification (see Appendix 7). To support this objective, three further exclusion criteria were established to ensure participation from individuals with the greatest need. Details of these can be found in Appendix 8.

Following referral individuals received a leaflet outlining the programme, including details on how to register. See Appendix 9.

2.3.3: Registration

The administration team at the LA received all referrals and these referrals were logged, creating a unique identification number. This unique identifier allowed data from various organisations to be collated to create a rich dataset.

As outlined in the leaflet (Appendix 9) individuals were responsible for phoning the LA administration team to register for the service. The individual's responsibility for registration is used as a proxy for "readiness to change" and allows for attrition prior to any payment from the commissioner (the LA) of the weight management service to the weight management provider of the programme (Slimming World). This ensures a certain level of cost efficiency within the programme although, arguably, may exclude individuals with greater need.

Registration also acts as a data gathering point. The variables collected at each stage of the programme are outlined in Appendix 10. Registration also allows for individuals to choose which specific weight management group they wish to join. Upon completion of registration, confirmation of where and when to attend their chosen group is sent to the individual.

2.3.4: Weight management service

Details of the procurement process can be found in Appendix 12. The successful bidder for the weight management contract and, thus, the provider of the service was Slimming World. Slimming World is a national, commercial organisation providing weight management services both to privately paying individuals and publically funded "Slimming on Referral" interventions. No distinction is made been these two client bases with both accessing the same resources and attending the same weekly group sessions. The benefit of this provision is the organisation's ability to provide continuous service delivery with no delays to participation; once an individual has selected a group they are able to commence participation the same week. Further, in County Durham and Darlington there are over 130 groups, most often held in community buildings (such as sport centres and community halls), providing wide geographical access. Sessions are delivered at various times during the day, evening and at weekends, further reducing barriers to participation.

Upon receiving their voucher, individuals attended their first session at which they exchange the voucher for a membership card entitling them to 12 weeks access to any Slimming World group. A healthy eating plan, physical activity opportunities and behaviour change strategies were discussed within the groups and resources were provided to support these objectives. Crucially, each week members were weighed by the consultant using their membership card and wireless electronic scales to allow Slimming World and the individual to record and monitor progress. This process ensures the accuracy of reported weight measurements and results in a rich dataset of attendance and weight change which Slimming World provided on a monthly basis to the LA.

Six contractual Key Performance Indicators (KPIs) were established to measure the effectiveness of the service (see Table 2.2). The outcomes of KPIs 1 and 2 are explored further in sections 3.4 and 2.6 respectively.

KPI	Indicator	Description	Threshold
1	Completion	Number of individuals who complete the programme i.e. attend 10 or more sessions.	50% of individuals to complete
2	Weight loss	Number of individuals who lose ≥5% of their initial body weight.	≥5% body weight loss for patients completing the programme
3	Data return	Individual's outcomes from the programme to be provided to the commissioner.	Data is supplied to the LA within 5 months from initial registration
4	Patient satisfaction	Patient satisfaction with the programme.	≥80% of respondents to the service user experience survey reporting "satisfied" or "very satisfied" to questions 1 to 4. [12]
5	Patient knowledge and behaviour	Patient's self-reported health behaviours.	≥80% of respondents to the service user experience survey answer "yes" to questions 5a and 6a.[13]
6	The minimum dataset (MDS)	Ongoing data on outcomes of the programme.	MDS supplied to the LA on a monthly basis

Table 2.2: Contractual key performance indicators for the weight management provider

[12] Question 1: "Overall how satisfied are you with the programme?" Question 2: "Overall how satisfied are you with the venue?" Question 3: "Overall how satisfied are you with the consultant?" and Question 4: Overall how satisfied are you with the content of the programme?". See Appendix 11 for the Service User Experience Survey.

[13] Question 5: "As a result of the programme do you have the knowledge to eat more healthily?" and Question 6: "As a result of the programme you eat more healthily?" See Appendix 11 for the Service User Experience Survey.

2.4: Descriptive statistics

This section presents and defines (1) weight outcomes, (2) attrition and (3) the characteristics of the sample. All referrals to the weight management programme between May 2012 and November 2013 were included. After data cleansing[14], records for 2,892 individuals were suitable for inclusion.

2.4.1: Weight

2.4.1.1: Overall weight and BMI

Weight is recorded at referral and at each of the 12 sessions of the service. Table 2.3 presents the average weight (kg) and BMI of individuals for each stage of the programme. Average weight at time of referral is 96.0kgs (SD ±17.2kg). Between referral and starting the service we observe an insignificant change of -0.09kg. Over the 12 weeks of the programme, however, we observe a relative consistent week-by-week decrease in weight from 95.9kg (±16.7kg) in the first week of the service, to 89.8kg (±16.1) observed at week twelve, the final week of the service. There is some evidence of higher weight loss in the earlier weeks of the service compared with the latter weeks highlighted by the slight curvature of the plotted outcomes (see Figure 2.3).

Average BMI at time of referral is 35.6 (SD ±5.3). Between referral and starting the starting we observe a slight but insignificant increase in BMI of 0.14. Over the 12 weeks of the service average BMI follows a similar downward trend where we observe an initial average of 35.8 (±5.13) in week one to 33.6 (SD±5.2) in week 12, the final week (see Figure 2.4).

[14] Data cleansing including the removal of test, erroneous and duplicate records, checking for incomplete records, ensuring all paper based records had been translated to the database and completing easily available missing information, for example, calculating BMI where height and weight were recorded.

Stage	Weight (kg)			BMI		
	n	Mean	Std. Dev.	n	Mean	Std. Dev.
Referral	2872	96.03	17.15	2871	35.61	5.25
Start of service	2087	95.94	16.65	2085	35.75	5.13
Week 2	1976	94.45	16.32	1972	35.20	5.06
Week 3	1832	93.62	16.01	1828	34.96	5.12
Week 4	1769	93.15	16.38	1765	34.77	5.17
Week 5	1677	92.61	16.23	1675	34.54	5.11
Week 6	1591	92.08	16.06	1587	34.34	5.06
Week 7	1519	91.51	16.29	1516	34.12	5.05
Week 8	1465	91.38	16.27	1462	34.11	5.10
Week 9	1391	91.14	16.46	1388	33.98	5.13
Week 10	1312	90.58	16.14	1310	33.83	5.19
Week 11	1240	90.43	16.24	1238	33.74	5.19
End of service	1150	89.82	16.13	1148	33.59	5.23

Table 2.3: Weight and BMI progression

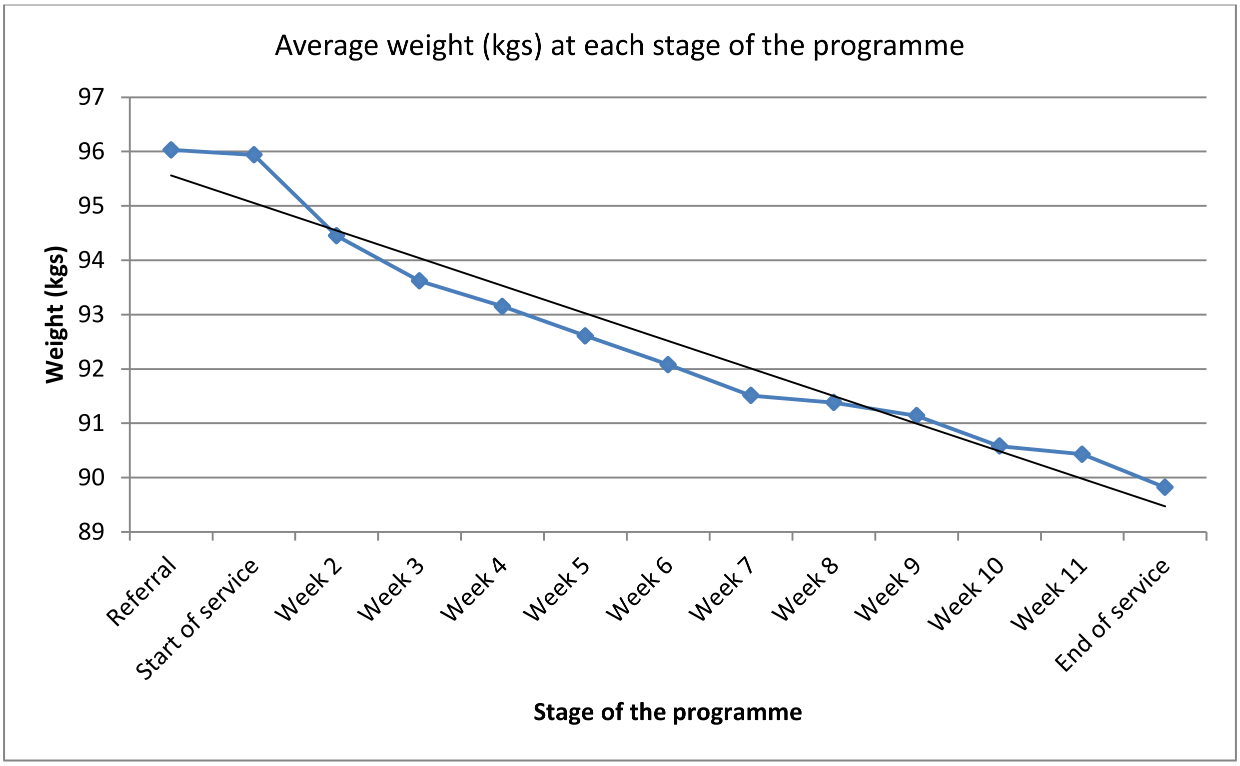

Figure 2.3: Average weight (kg) of individuals at each stage of the programme

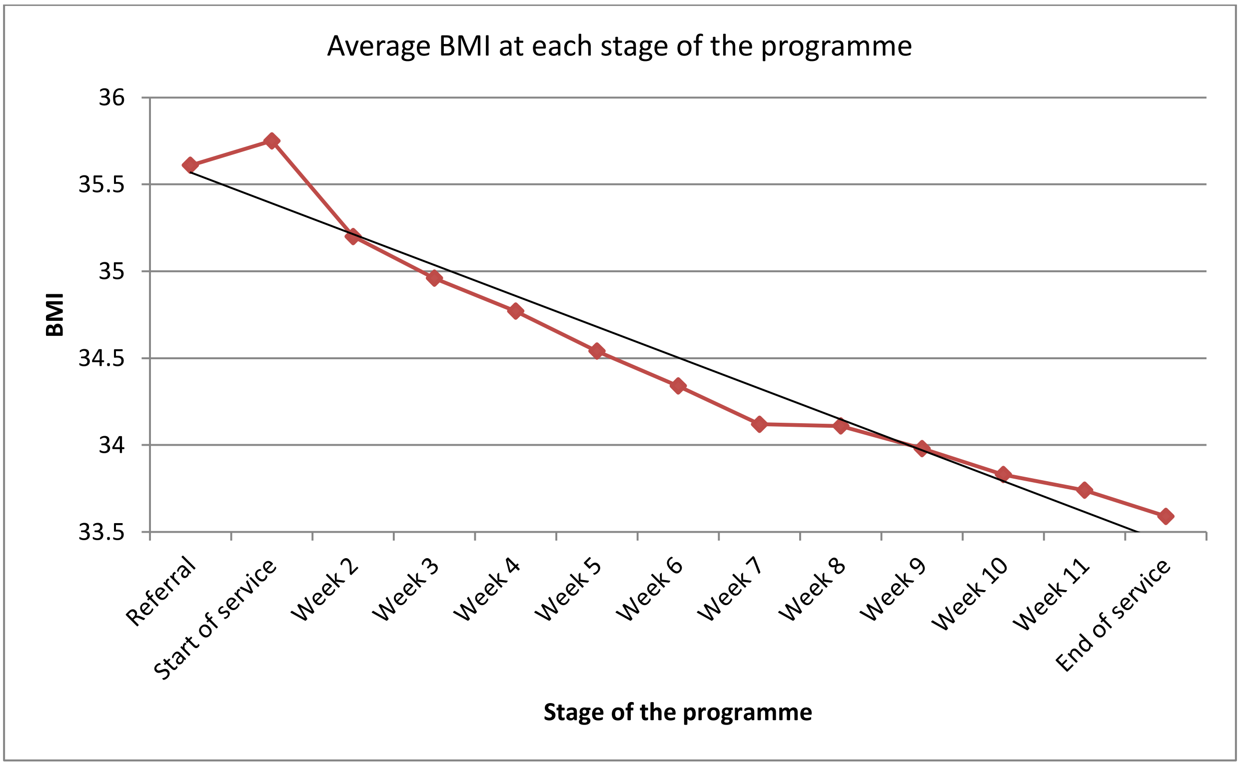

Figure 2.4: Average BMI of individuals at each stage of the programme

2.4.1.2: Defining the weight outcomes

We focus on three key outcome variables.

1. Percentage weight change
    a. A continuous variable of weight change between week 1 and week 12 of the service.
2. BMI change (continuous variable)
    a. A continuous variable of BMI change between week 1 and week 12 of the service.
3. Significant weight loss
    a. A binary variable where 1=an individual who loses ≥5% of baseline weight.[15]

These weight outcomes are explored at two significant time points; engagement at week 10 and engagement at week 12.

As presented in Table 2.3 and discussed further in Chapter 3, we observe significant attrition throughout the 12 weeks of the service. In total, 2,087 individuals start the service. Only 1,312 attend week 10 and 1,150 attend the final session representing attrition rates of 37% and 45% respectively. This presents a challenge of how to deal with a large proportion of missing data.

[15] The recommended rate of weight loss is between 0.5-1kg per week. To significantly reduce the probability of future development of co-morbidities, the recommended overall weight loss for a 12 week weight loss programme is between 5% and 10% of initial body weight (NICE, 2014 and US DHHS, 2010).

Popular methods for dealing with attrition in weight management service evaluation include:

1. Last Observation Carried Forward (LOCF) methodologies.
    - The last recorded weight is used in place of the missing value.
2. Baseline Observation Carried Forward (BOCF) methodologies.
    - It is assumed the individual's weight returns to baseline measurement and this is used in place of the missing value.
3. Imputation methodologies.
    - Missing values are estimated using prior observed trends in an individual's weight and projecting these trends to impute a value.

Chapter 4 discusses each of the above methodologies in more detail, including the limitations of each, and presents a superior methodology for dealing with missing values resulting from attrition. In this current chapter, however, we exclude individuals who are not engaged in weeks 10 and 12 from analyses and concentrate on exploring factors associated with successful weight loss.

2.4.1.3: Estimating weight outcomes at week 10

Attendance is a measure of the quantity of sessions at which an individual is present. Whilst consistent attendance was encouraged, individuals were able attend sessions subsequent to a period of non-attendance. An individual may, for example, not attend sessions 2 and 3 but attend sessions 4 to 12. Engagement, therefore, is a measure of the duration of participation, determined by an individual's final week of attendance. Whilst an individual may not attend week 10, for example, attendance at week 11 and/or 12 indicates continued engagement at this point in time. An individual is therefore, said to be engaged at week ten if they attend week 10, 11 and/or 12.

To illustrate, Figure 2.5 compares participation throughout the service defined by attendance and engagement. At week six, for example, 76% of individuals attended the session, however, 85% of individuals are still engaged in the service, evidenced by attendance to subsequent sessions.

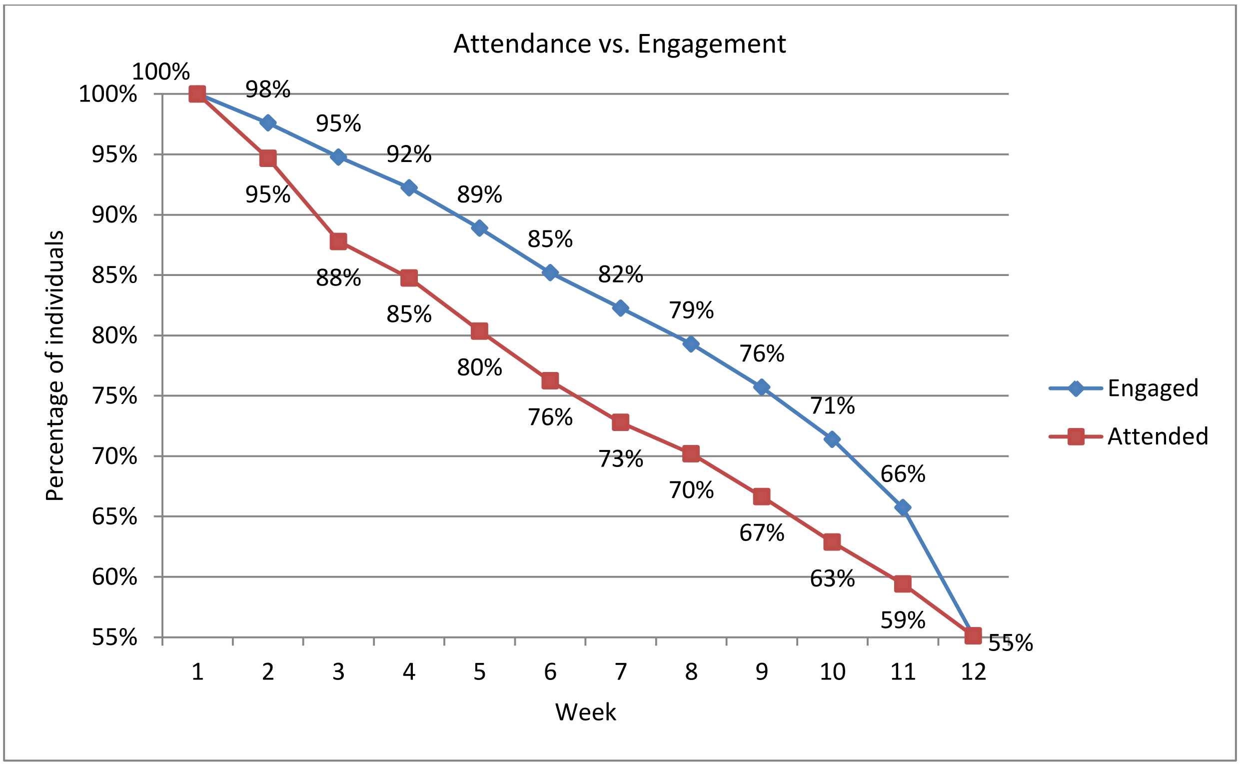

Figure 2.5: Participation by attendance and engagement

As week 12 is the final session of the service, engagement at week 12 is equal to attendance at week 12. Engagement at week 10 (n=1490), however, does not equal attendance at week 10 (n=1312) and, thus, weight outcomes for non-attending but engaged individuals must be estimated.

Estimates were made using weight measurements from previous and subsequent attendances, assuming consistent linear weight change. Table 2.4 outlines the weeks used to estimate weight outcomes at week 10. Of the 1,490 individuals engaged at week 10, 88% attended week 10 and, thus, had their weight measured and recorded. Eight percent of individuals missed week 10 but attended weeks 9 and 11 and, thus, these measurements were used to estimate weight at week 10. A further 4% of individuals attended weeks 8 and 11 or 9 and 12 resulting in less than 1% of estimated weight outcomes at week 10 being based on a gap in attendance larger than 2 weeks. The estimated weights are, therefore, considered to represent a fairly accurate approximation of outcomes at this stage to the extent that weight change is gradual and smooth.

Previous week measurement	**Subsequent week measurement**	**n=**	**% of individuals**
10	10	1312	88%
9	11	115	8%
8	11	23	2%
7	11	6	0%
6	11	2	0%
5	11	1	0%
9	12	29	2%
8	12	1	0%
7	12	1	0%
TOTAL		1,490	100%

Table 2.4: Weeks used to estimate weight outcomes at week 10

2.4.2: Attrition

One criticism of research exploring factors associated with weight loss is the analysis of outcomes of only completers rather than all individuals who start programmes (Franz et al., 2007). The value to policy makers of analyses restricted to completers of obesity services is limited. In many circumstances policy makers may be more interested in the outcomes of the individuals who do not succeed in completing the programme as these are likely to form the target for policy development such as new services and the introduction of incentives. This section acknowledges and describes the broader sample of individuals engaged in the programme and, whilst, this chapter explores only outcomes of completers, the following two chapters explore and address the issue of attrition.

Figure 2.6 describes attrition throughout the programme. It outlines the number of individuals engaged at each stage, the percentage of the total sample this represents and the percentage of the sample for the given stage. In summary, 18% of individuals dropout after being referred, a further 10% dropout after registration and a further 32% dropout at some point during the 12 week service. This results in an overall attrition rate of 60%.

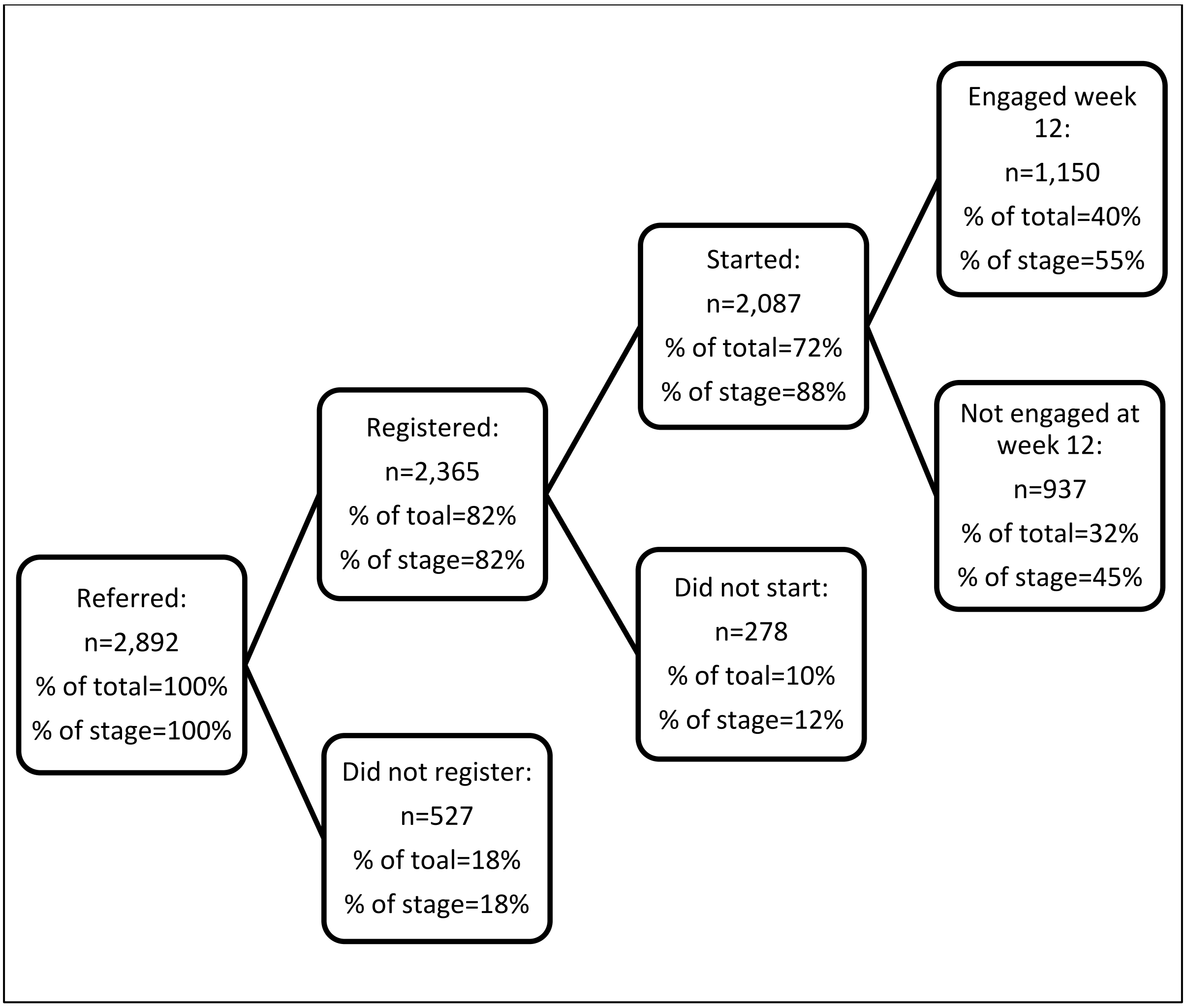

Figure 2.6: Attrition throughout the programme

Previously, Figure 2.5 presented participation across the 12 weeks of the service, comparing attrition defined by attendance to attrition defined by engagement. In both definitions attrition was observed to be relatively consistent throughout the service with an average of 4% dropout week-on-week.

2.4.3: Individual characteristics

Table 2.5 details the independent variables explored in the analysis. The number of observations and means are provided for each variable. Variables are collected at several stages across the programme, partly explaining variations in the number of observations (n).

Details of the stage of the programme at which each variable was collected, and a full overview of variables collected, at can be found in Appendix 12. In total, thirty-one variables explore a broad range of topics associated with weight loss including socio-demographic, weight, aspects of the programme, health behaviours, physical health, mental health and personality factors.

	n	Mean	SD	Details
Socio-Demographics				
Male	2875	0.10	0.30	Binary variable where 0=male and 1=female
Age	2873	46.57	14.59	Continuous variable. Age in years at time of referral.
White (ethnicity)	2825	0.99	0.10	Binary variable where 0=non-white ethnicity and 1=white ethnicity.
Indices of deprivation	2832	4.45	2.46	Categorical variable. Measure of deprivation.
Partner	2307	0.63	0.48	Binary variable where 0=no partner and 1=partner.
Presence of children	2304	0.83	0.38	Binary variable where 0=no children and 1=children.
Employed	2282	0.53	0.50	Binary variable where 0=unemployed and 1=employed.
Degree	2289	0.16	0.37	Binary variable where 0=no degree and 1=degree qualification or higher
Perception of local area	2275	63.45	16.82	Continuous variable. Measure of local exercise and healthy eating opportunities.
Weight factors				
BMI (at referral)	2871	35.60	5.25	Continuous variable. BMI at time of referral.
Weight change at week 2	1976	-3.25	2.26	Continuous variable. Weight change in kg between week 1 and week 2.
Aspects of the service				
Self-referral	2892	0.38	0.49	Binary variable where 0=healthcare or medical referral and 1=self-referral.
Days referral to registration	2299	13.85	12.88	Continuous variable. Number of days between referral and registration.
Days registration to start	2043	13.04	9.13	Continuous variable. Number of days between registration and starting the service.
Consistent attendance	2087	0.54	0.50	Binary variable where 0=inconsistent attendance and 1=consistent attendance.
Health behaviours (continued on next page)				

Smokes	2689	0.13	0.34	Binary variable where 0=non-smoker and 1=current smoker
Excess alcohol consumption	2661	0.09	0.28	Binary variable where 0=drinks within, and 1=drinks above, recommendations
Perception of diet	2281	61.84	17.18	Continuous variable. Measure of self-perception of diet at time of registration.
Energy expenditure (kcal/day)	2270	3483	782	Estimated daily energy expenditure in kcal.
Physical health				
Disabled	2764	0.05	0.21	Binary variable where 0=no disability and 1=registered as disabled
Cardiovascular disease	2892	0.08	0.27	Binary variable where 0=no diagnosed CVD and 1=diagnosed with CVD.
Mobility co-morbidities	2892	0.21	0.41	Binary variable where 0=no diagnosed conditions and 1=diagnosed condition.
Diabetes	2892	0.11	0.31	Binary variable where 0=does not have diabetes 1=diagnosed with diabetes.
Hypertension	2892	0.21	0.41	Binary variable where 0=no hypertension and 1=diagnosed hypertension.
Mental health				
Depression	2892	0.12	0.33	Binary variable where 0=no depression and 1=diagnosed depression.
Stress and anxiety	2892	0.07	0.26	Binary variable where 0=no stress/anxiety and 1=diagnosed stress/anxiety.
Personality				
Openness	2260	59.56	22.27	Continuous variable. Measure of openness.
Neuroticism	2260	48.98	23.43	Continuous variable. Measure of neuroticism.
Conscientiousness	2260	73.14	18.16	Continuous variable. Measure of conscientiousness.
Agreeableness	2260	73.71	17.72	Continuous variable. Measure of agreeableness.
Extroversion	2260	37.88	23.19	Continuous variable. Measure of extroversion.

Table 2.5: Outline of variables for analysis

Further details on selected variables are provided below for clarification.

2.4.3.1: Socio-Demographics

Ethnicity

The ONS (Office of National Statistics) recommended ethnic group question for use on surveys in England (ONS, 2016) was applied at the referral stage. It consists of five categories which are presented in Appendix 10. Only 30 (<1%) individuals were record as being non-white. This is reflective of the 2011 census data which finds similar prevalence levels in the population of County Durham and Darlington from which the sample of referred individuals are drawn; 97% of the total population of County Durham and Darlington recorded as white.

Deprivation

Individual's postcodes were used to obtain indices of deprivation; a relative measure of deprivation by small geographical areas known as Lower Super Output Areas (LOSAs). There are 32,482 LOSAs in England which are scored, ranked and subsequently divided into 10 equal groups (deciles). Decile 1 indicates the most deprived areas with decile 10 indicating lowest deprivation (DCLG, 2016). Table 2.6 presents the distribution of individuals in the weight management programme across the deciles and compare this to the population level distribution in County Durham. We observe similar distributions, with some evidence of overrepresentation of individuals in deciles 3 and 5, and some evidence of underrepresentation in deciles 1 and 9. Overall, however, we achieve a relatively representative spread of individuals from areas of high, average and low deprivation areas.

Indices	n=	Percentage of sample	Percentage of total population
1	185	6.5%	11.4%
2	496	17.5%	17.1%
3	600	21.2%	16.9%
4	389	13.7%	13.8%
5	320	11.3%	8.8%
6	209	7.4%	7.4%
7	201	7.1%	6.7%
8	194	6.9%	6.1%
9	111	3.9%	7.2%
10	127	4.5%	4.4%

Table 2.6: Distribution of individuals across indices of deprivation[16]

Perception of local area

Perception of local area was measured by taking the average score of nine questions asking individuals to rate their local area on features such as the availability of healthy food and opportunities for physical activity. A score of 100 represents a perception of a healthy area with a score of 0 representing a perception of an unhealthy area. Details of the questions can be found in Appendix 10.

[16] County level deprivation scores retrieved from Durham County Council (2010).

2.4.3.2: Aspects of the service

Self-referral

At the referral stage the healthcare professional was asked to indicate the reason for the referral; (1) patient request, (2) health professional referral, (3) underlying health condition or (4) weight loss required for health intervention. The former three options were grouped to create the binary variable where 0=medical or healthcare professional referral and 1=self-referral.

Time

The average timescale for participation is detailed in Table 2.7. The time from referral to registration varies greatly with some individuals registering the same day as their referral whilst some individuals take up to two months to contact the administration team to register. Similar variations are seen in times between registration and starting. The average time from referral to registration and registration to starting is 14 and 13 days respectively.

Stage	Start	End	Days
1	Referral	Registration	14
2	Registration	Start programme	13
3	Start programme	End programme	84
Total			111

Table 2.7: Average timescale for participation throughout the programme

Consistency of attendance

Consistent attendance is recorded as a binary variable. An individual is considered a consistent attendee if they demonstrate no breaks in attendance between the start week and their final week of attendance. For further clarity; an individual is considered a consistent attendee even if they do not, for example, attend after week 6 so long as they have attended all sessions up to this point i.e. they have one period of consistent attendance. An individual is considered an inconsistent attendee if they demonstrate 1 or more weeks of absence between the start week and their final week of attendance. Overall 54% of individuals will consistently attend.

2.4.3.3: Health behaviours

Smoking

Smoking status was determined by the number of cigarettes smoked per day. A binary variable was created where 0 indicates a non-smoker and 1 indicates an individual who smokes one or more cigarettes per day; 13% of individuals are categorised as smokers.

Alcohol consumption

Alcohol consumption was measured by estimated units per week consumed. This was subsequently transformed into a binary variable where 1 indicates an individual who drinks above the recommended maximum recommended units of alcohol per week (>21 units per week for men and >14 units per week for women).

Perception of diet

Perception of diet was measured by taking the average score of ten questions asking individuals to rate aspects of their diet, such as food portions and awareness of calories in food. A score of 100 represents a perceived healthy diet with a score of 0 representing a perceived unhealthy diet. Details of the questions can be found in Appendix 10.

Energy expenditure

Daily energy expenditure was measured using the Stanford 7 day recall. The Stanford 7-day Physical Activity Recall Scale (PAR) estimates daily energy expenditure in kilocalories (kcal). For each day of the past week, participants report the approximate number of hours they slept and spent in moderate, hard, and very hard activity. The PAR measures all forms of energy expenditure including purposeful exercising, playing sports or doing household chores (Sallis et al., 1985). Details of this estimation method can be found in Appendix 10.

2.4.3.4: Physical health

Information regarding disability, CVD, stroke, heart disease, arthritis, hypertension, asthma/Chronic Obstructive Pulmonary Disease (COPD), Musculoskeletal (MSK) conditions, diabetes, joint problems and back problems were collected as binary variables. CVD, heart disease and stroke were combined into one variable "CHD" as were arthritis, joint problems and back problems into a "mobility co-morbidity" group. Overall, 5% of the sample is disabled, 8% have CHD conditions, 21% have mobility co-morbidities, 11% are diabetics and 21% have hypertension.

2.4.3.5: Mental Health

Depression and stress/anxiety are binary measures of the presence of these mental health conditions. Professionals referring to the service were responsible for determining the presence of a mental health condition. Due to the majority of referrals being made by GPs or Practice Nurses, the presence of a mental health condition was almost always drawn from an individual's health record. Overall 12% of individuals referred had depression and 7% had stress or anxiety.

2.4.3.6: Personality

Personality was measured using the Big Five Inventory (BFI) (Gosling, Rentfrow, and Swann, 2003). Scores out of 100 were obtained for measures of openness, neuroticism, conscientiousness, agreeableness and extroversion. Average scores are 59.56, 49.98, 73.14, 73.71 and 37.88 respectively. Details of the questions asked to elicit personality scores can be found in Appendix 10.

2.4.3.7: Missing Data

One issue that arise with this type of work is missing data at various stages of the process. Before presenting the results of this chapter we outline our acknowledgement and management of this potential issue. During the data collection and cleaning process all attempts were made to minimise missing data, however, due to the number of variables and numerous sources of data obtaining a full record for individuals was often not possible. Table 2.8 provides an overview of observations at each stage of the programme by individual explanatory variable. The variable 'self-referral', for example, contains no missing data as the number of data point (i.e. the number of observations) reported at each stage matches the number of observations for the variable ‘record’ (i.e. a count of every individual with have a record for) presented at the top of the table.

	Referral		Registration		Week 1		Week 10		Week 12	
	n=	Mean	n=	Mean	n=	Mean	n=	Mean	n=	Mean
Record	2892	1	2365	1	2087	1	1490	1	1150	1
Socio-Demographics										
Male	2875	0.10	2355	0.09	2079	0.08	1486	0.09	1147	0.09
Age	2873	46.57	2356	47.04	2079	47.48	1486	48.62	1147	49.27
White (ethnicity)	2825	0.99	2318	0.99	2046	0.99	1460	0.99	1127	0.99
Indices of deprivation	2832	4.45	2329	4.50	2056	4.53	1474	4.57	1137	4.65
Partner	-	-	2307	0.63	2042	0.65	1461	0.66	1130	0.65
Presence of children	-	-	2304	0.83	2040	0.83	1458	0.82	1127	0.82
Employed	-	-	2282	0.53	2020	0.54	1444	0.54	1118	0.53
Degree	-	-	2289	0.16	2026	0.17	1451	0.18	1122	0.18
Perception of local area[1]	-	-	2275	63.44	2013	63.77	1438	64.34	1111	64.33
Weight factors										
BMI (at referral)	2871	35.61	2349	35.51	2073	35.49	1481	35.60	1142	35.69
Weight change at week 2	-	-	-	-	1976	-3.25	1466	-3.45	1136	-3.55
Aspects of the service										
Self-referral	2892	0.38	2365	0.39	2087	0.39	1490	0.39	1150	0.39
Days referral to registration	2299	13.85	2299	13.85	2028	12.77	1454	12.67	1123	12.44
Days registration to start	-	-	-	-	2043	13.04	1461	12.56	1128	12.38
Consistent attendance	-	-	-	-	2087	0.54	1490	0.55	1150	0.60
Health behaviours										
Smokes	2689	0.13	2207	0.12	1944	0.11	1389	0.09	1070	0.09
Excess alcohol consumption	2661	0.09	2196	0.09	1939	0.09	1395	0.09	1076	0.08
Perception of diet[1]	-	-	2281	61.84	2015	62.37	1441	63.52	1116	63.42
Energy expenditure (kcal/day)	-	-	2270	3483.12	2011	3469.45	1436	3458.82	1111	3456.09

[continued on next page]

Physical health										
Disabled	2764	0.05	2267	0.05	2001	0.05	1426	0.05	1101	0.05
Cardiovascular disease	2892	0.08	2365	0.07	2087	0.07	1490	0.08	1150	0.08
Mobility co-morbidities	2892	0.21	2365	0.22	2087	0.22	1490	0.24	1150	0.25
Diabetes	2892	0.11	2365	0.10	2087	0.10	1490	0.11	1150	0.11
Hypertension	2892	0.21	2365	0.21	2087	0.22	1490	0.23	1150	0.23
Mental health										
Depression	2892	0.12	2365	0.12	2087	0.11	1490	0.11	1150	0.11
Stress and anxiety	2892	0.07	2365	0.07	2087	0.07	1490	0.07	1150	0.06
Personality										
Openness[1]	-	-	2260	59.55	2002	59.54	1430	59.90	1105	59.31
Neuroticism[1]	-	-	2260	48.98	2002	48.75	1430	48.14	1105	48.23
Conscientiousness[1]	-	-	2260	73.14	2002	73.19	1430	73.30	1105	73.14
Agreeableness[1]	-	-	2260	73.72	2002	73.56	1430	73.35	1105	73.17
Extroversion[1]	-	-	2260	37.87	2002	37.89	1430	37.79	1105	38.09

Table 2.8: Number of recorded variables for each variable in the analyses and each stage of the weight management service

A complete record for an individual, enabling the analyses presented in Chapter 2, 3 and 4, consists of thirty-two explanatory variables and eight dependant variables. A complete dataset for the 2,087 individual in our sample would, therefore, consist of 83,480 data points. Missing data represents <2% of these data points. Further, the records for majority of individuals (97%) within our analyses contain three of fewer missing data points. The greater issues is, however, that regression analyses exclude an individual if any data point is missing and, thus, within our analyses this results in the exclusion of 26% of individuals.

There is no established threshold within the literature regarding an acceptable percentage of missing data (Dong and Peng, 2013). Shafer (1999) argues that a missing rate of 5% or less will have little impact on the data whilst Bennett (2001) proposes a threshold of 10%. More recent discussions have, however, posited that is not the amount of missing data but the pattern of missing data that will have a greater impact on research results (Tabachnick, Fidell and Osterlind, 2001).

To address the issue of missing data we first establish variables of concern. Percentage of missing data is calculated for each of the 32 explanatory variables. Two variables are highlighted as a potential concern. These variables are 'smokes' and 'excess alcohol consumption' where data is missing for 7% and 6% of individuals respectively. These variables are collected at the referral stage of the process. In some cases healthcare professionals manually entered data for these variables, however, the referral forms were built into IT systems and were able to pull information from existing records.

The key question is whether we can say these data are missing at random. Missing at random (MAR) refers to missing data that is unrelated to the actual values had the data been observed (Rubin, 1976). Within our research, the accidental miscoding of a variable resulting in a missing data point, for example, is unlikely to be related to the actual value. If data points are randomly missed then missing data leads to no bias in the estimated coefficients only higher standard errors. If missing data points are correlated with independent variables, then we have bias in the estimated coefficients. A reduced sample due to data that are MAR can be viewed as a smaller but representative sample of the original data set. Not missing at random (NMAR) refer to missing data that is related to the actual values had the data not been missing (Rubin, 1976). Within our research, if participants systematically refuse to answer a question, for example, this would be classified as NMAR as the missing data is not occurring at random. Data which is NMAR is likely to introduce bias into regression models and, thus, needs to be acknowledged and addressed within research.

Smokes

To investigate whether the variable 'smokes' is MAR, we first define a new binary variable which indicates whether the variable is observed (=1) or missing (=0). We then fit a probit regression model for the newly generated variable with our other observed variables[17] as covariates. Through this sensitivity check we find some evidence of a relationship between initial BMI and the probability of missing data in the 'smoke' variable (β=-.04 *p*-value=0.05). This suggests that to some extent the missingness of data in the 'smokes' variable can be

[17] Gender, age, ethnicity, deprivation score, partner, presence of children, employed, degree, perception of local area, BMI at referral, weight change at week 2, self-referral, time between stages of the programme, consistent attendance, excess alcohol consumption, diet score, energy expenditure score, disability, CVD, mobility co-morbidities, diabetes, hypertension, depression, stress and personality scores.

predicted by initial BMI with a higher initial BMI being related to an increased probability of an observed measure of the variable ‘smokes’.

Excess alcohol consumption

To investigate whether the variable ‘excess alcohol consumption’ is MAR, we first define a binary variables which indicates whether the variable is observed (=1) or missing (=0). We then fit a probit regression model for the newly generated variable with our other observed variables are covariates. Through this sensitivity check we find no evidence of a relationship between the variables in our model and the probability of missing data in the ‘excess alcohol consumption’ variable.

In conclusion, we find little to no evidence for the presence of variables which are NMAR and whilst we acknowledge a substantial number of individuals are excluded from analyses our sensitivity checks reveal that the sample utilised within our analyses is likely to be an unbiased sub-set of the original complete dataset. The following chapter presents variables associated with attrition and aims to identify whether there are observable variables that determine attendance to the service. Further, in Chapter 4 we apply statistical methods to examine whether an unobserved variable(s) is significant to both engagement and weight loss outcomes, thus, whether attrition is non-random.

2.5: Results

2.5.1: Overview

The following tables present the results of the regressions. Maximum likelihood estimations explore the associations between variables outlined in section 2.4.3 with the outcome variable 'significant weight loss'. Ordinary Least Squares (OLS) explore the associations between variables outlined in section 2.4.3 with the outcome variables 'percentage weight change' and 'BMI change'. The first three tables present the results for those engaged at week 10 with the second set of three tables reporting the results for those engaged at week 12. A summary of what is reported in the results tables is outlined in Table 2.9 below.

Table No.	Dependent Variable	Explanatory Variables	Sample	Estimation Method
2.10	Percentage Weight Loss	32 variables outlined in section 2.4.3.	Individuals engaged at week 10	OLS
2.11	BMI Change	32 variables outlined in section 2.4.3.	Individuals engaged at week 10	OLS
2.12	Significant Weight Loss	32 variables outlined in section 2.4.3.	Individuals engaged at week 10	Maximum Likelihood
2.13	Percentage Weight Loss	32 variables outlined in section 2.4.3.	Individuals engaged at week 12	OLS
2.14	BMI Change	32 variables outlined in section 2.4.3.	Individuals engaged at week 12	OLS
2.15	Significant Weight Loss	32 variables outlined in section 2.4.3.	Individuals engaged at week 12	Maximum Likelihood

Table 2.9: Summary of the Results Tables in Chapter 2

BMI and percentage weight change are continuous variables and, thus, are estimated using linear regression models.

$$y = \alpha + \beta x + \varepsilon$$

which specifies a linear relationship between the dependent variable y and the single explanatory variable x .

Significant weight loss is a binary variable and, thus is estimated using a probit model. The probit model is a regression where the dependent variable is binary. It employs a probit link function and is estimated using the maximum likelihood procedure. The probit function takes any argument between ±∞ and transforms it into a number between 0 and 1. The probit link function is:

$$\text{prob}(Y=1 \mid \mathbf{X}) = \Phi(\mathbf{X}'\beta) \qquad (1)$$

where **X** is a vector of individual characteristics and control variables, β is a vector of estimated coefficients and Φ is the cumulative standard normal distribution. One can link a latent index $y^* = \mathbf{X}'\beta + \varepsilon$ to the indicator variable y, which is equal to -1 or 1: y = 1 when $y^* > 0$, and otherwise y is equal to −1. The conditional log-likelihood is then

$$\ln L(\beta\, ; y, \mathbf{X}) = \textstyle\sum_i \left[(\ln \Phi(\mathbf{X}'\beta) \times \mathbf{I}(y_i = 1)) + (\ln (1- \Phi(\mathbf{X}'\beta))\times\mathbf{I}(y_i = -1)) \right] \qquad (2)$$

where **I**(·) is the indicator function, and y_i =1(−1) denotes the choice. The latent index y* is defined as a linear function of the characteristics in vector **X**.

Table 2.10: Percentage weight change of individuals engaged at week 10
OLS Regression (n=1,100)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	-1.25	1.38	0.37	-3.96	1.46
Demographics					
Male	-0.33	0.29	0.25	-0.90	0.23
Age	-0.08	0.04	0.03	-0.15	-0.01
Age squared	0.00	0.00	0.14	0.00	0.00
White (ethnicity)	-1.45	0.74	0.05	-2.90	0.01
Deprivation score	-0.03	0.03	0.30	-0.10	0.03
Partner	-0.18	0.17	0.29	-0.52	0.15
Presence of Children	0.30	0.22	0.17	-0.13	0.72
Employed	0.29	0.18	0.12	-0.07	0.65
Degree level education	-0.73	0.20	0.00	-1.14	-0.33
Perception of local area	0.00	0.01	0.97	-0.01	0.01
Weight factors					
BMI (initial)	0.05	0.02	0.01	0.01	0.09
Weight change (kg) week 2	0.63	0.03	0.00	0.57	0.70
Aspect of the programme					
Self-referred	-0.31	0.16	0.05	-0.62	0.00
Days (referral to registration)	-0.01	0.01	0.16	-0.02	0.00
Days (registration to start)	-0.02	0.01	0.06	-0.04	0.00
Consistent attendance	-1.59	0.16	0.00	-1.89	-1.28
Health behaviours					
Smokes	-0.57	0.28	0.04	-1.11	-0.02
Excess alcohol consumption	0.59	0.27	0.03	0.05	1.12
Perception of diet	0.01	0.01	0.01	0.00	0.03
Energy expenditure (kcal/day)	0.00	0.00	0.10	0.00	0.00
Physical health					
Disabled	-0.17	0.36	0.64	-0.89	0.54
Cardiovascular disease	0.15	0.30	0.63	-0.44	0.73
Mobility problems	0.25	0.19	0.20	-0.13	0.62
Diabetes	0.41	0.26	0.11	-0.10	0.91
Hypertension	0.03	0.20	0.88	-0.37	0.43
Mental health					
Depression	0.21	0.28	0.46	-0.34	0.76
Stress	0.04	0.32	0.90	-0.59	0.67
Personality					
Openness	0.00	0.00	0.89	-0.01	0.01
Neuroticism	0.00	0.00	0.70	-0.01	0.01
Conscientiousness	0.00	0.00	0.60	-0.01	0.01
Agreeableness	0.00	0.00	0.79	-0.01	0.01
Extroversion	0.00	0.00	0.27	-0.01	0.00

Table 2.11: BMI change of individuals engaged at week 10
OLS Regression (n=1,100)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	1.14	0.79	0.15	0.41	2.70
Demographics					
Male	-0.24	0.17	0.15	-0.56	0.09
Age	-0.01	0.02	0.53	-0.06	0.03
Age squared	0.00	0.00	0.70	0.00	0.00
White (ethnicity)	-0.57	0.42	0.18	-1.41	0.26
Indices of deprivation	-0.01	0.02	0.50	-0.05	0.02
Partner	-0.05	0.10	0.64	-0.24	0.15
Presence of Children	0.12	0.12	0.35	-0.13	0.36
Employed	0.04	0.11	0.70	-0.17	0.25
Degree level education	-0.12	0.12	0.31	-0.35	0.11
Perception of local area	0.00	0.00	0.32	0.00	0.01
Weight factors					
BMI (initial)	-0.04	0.01	0.00	-0.06	-0.02
Weight change (kg) week 2	0.23	0.02	0.00	0.19	0.27
Aspect of the programme					
Self-referred	-0.15	0.09	0.10	-0.33	0.03
Days (referral to registration)	0.00	0.00	0.48	-0.01	0.00
Days (registration to start)	-0.01	0.01	0.05	-0.02	0.00
Consistent attendance	-0.62	0.09	0.00	-0.79	-0.44
Health behaviours					
Smokes	-0.40	0.16	0.01	-0.71	-0.09
Excess alcohol consumption	0.23	0.16	0.15	-0.08	0.53
Perception of diet	0.00	0.00	0.32	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.39	0.00	0.00
Physical health					
Disabled	-0.25	0.21	0.23	-0.66	0.16
Cardiovascular disease	0.44	0.17	0.01	0.11	0.78
Mobility problems	0.02	0.11	0.84	-0.19	0.24
Diabetes	-0.03	0.15	0.84	-0.32	0.26
Hypertension	0.04	0.12	0.74	-0.19	0.27
Mental health					
Depression	0.17	0.16	0.28	-0.14	0.49
Stress	-0.12	0.18	0.52	-0.48	0.24
Personality					
Openness	0.00	0.00	0.80	0.00	0.00
Neuroticism	0.00	0.00	0.36	0.00	0.01
Conscientiousness	0.00	0.00	0.93	-0.01	0.00
Agreeableness	0.00	0.00	0.99	-0.01	0.01
Extroversion	0.00	0.00	0.08	-0.01	0.00

Table 2.12: Significant weight loss of individuals engaged at week 10
Maximum Likelihood Estimation (n=1,100)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	-1.30	0.76	0.09	-2.79	0.18
Demographics					
Male	0.12	0.16	0.45	-0.20	0.44
Age	0.03	0.02	0.18	-0.01	0.07
Age squared	0.00	0.00	0.34	0.00	0.00
White (ethnicity)	0.55	0.39	0.16	-0.22	1.32
Indices of deprivation	-0.02	0.02	0.34	-0.05	0.02
Partner	0.15	0.09	0.12	-0.04	0.33
Presence of Children	-0.16	0.12	0.17	-0.40	0.07
Employed	-0.17	0.10	0.10	-0.37	0.03
Degree level education	0.21	0.11	0.06	-0.01	0.43
Perception of local area	0.00	0.00	0.72	0.00	0.01
Weight factors					
BMI (initial)	-0.03	0.01	0.01	-0.05	-0.01
Weight change (kg) week 2	-0.25	0.02	0.00	-0.30	-0.21
Aspect of the programme					
Self-referred	0.17	0.09	0.06	0.00	0.34
Days (referral to registration)	0.00	0.00	0.64	-0.01	0.01
Days (registration to start)	0.01	0.01	0.03	0.00	0.02
Consistent attendance	0.61	0.08	0.00	0.44	0.77
Health behaviours					
Smokes	0.16	0.15	0.30	-0.14	0.46
Excess alcohol consumption	-0.21	0.15	0.15	-0.50	0.08
Perception of diet	0.00	0.00	0.11	-0.01	0.00
Energy expenditure (kcal/day)	0.00	0.00	0.40	0.00	0.00
Physical health					
Disabled	0.21	0.21	0.33	-0.21	0.62
Cardiovascular disease	-0.05	0.16	0.77	-0.37	0.27
Mobility problems	0.00	0.10	0.99	-0.20	0.20
Diabetes	-0.10	0.14	0.48	-0.37	0.18
Hypertension	0.07	0.11	0.51	-0.15	0.29
Mental health					
Depression	0.07	0.16	0.65	-0.24	0.38
Stress	-0.16	0.18	0.37	-0.51	0.19
Personality					
Openness	0.00	0.00	0.73	0.00	0.00
Neuroticism	0.00	0.00	0.80	0.00	0.00
Conscientiousness	0.00	0.00	0.48	0.00	0.01
Agreeableness	0.00	0.00	0.67	0.00	0.01
Extroversion	0.00	0.00	0.13	0.00	0.01

Table 2.13: Percentage weight change of individuals engaged at week 12
OLS Regression (n=852)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	0.28	1.82	0.88	-3.30	3.86
		Demographics			
Male	-0.31	0.37	0.41	-1.04	0.42
Age	-0.10	0.05	0.05	-0.19	0.00
Age squared	0.00	0.00	0.16	0.00	0.00
White (ethnicity)	-2.43	0.99	0.02	-4.38	-0.48
Indices of deprivation	-0.04	0.04	0.40	-0.12	0.05
Partner	-0.14	0.23	0.55	-0.58	0.31
Presence of Children	0.18	0.29	0.53	-0.39	0.75
Employed	0.14	0.25	0.57	-0.34	0.62
Degree level education	-0.73	0.28	0.01	-1.27	-0.19
Perception of local area	0.00	0.01	0.51	-0.02	0.01
		Weight factors			
BMI (initial)	0.07	0.03	0.01	0.02	0.12
Weight change (kg) week 2	0.71	0.05	0.00	0.62	0.80
		Aspect of the programme			
Self-referred	-0.25	0.21	0.23	-0.66	0.16
Days (referral to registration)	-0.01	0.01	0.52	-0.02	0.01
Days (registration to start)	-0.02	0.01	0.05	-0.05	0.00
Consistent attendance	-1.98	0.21	0.00	-2.39	-1.57
		Health behaviours			
Smokes	-0.68	0.37	0.07	-1.42	0.05
Excess alcohol consumption	0.46	0.38	0.22	-0.28	1.20
Perception of diet	0.01	0.01	0.12	0.00	0.02
Energy expenditure (kcal/day)	0.00	0.00	0.57	0.00	0.00
		Physical health			
Disabled	-0.33	0.49	0.50	-1.30	0.63
Cardiovascular disease	0.20	0.38	0.61	-0.55	0.94
Mobility problems	0.12	0.25	0.63	-0.37	0.62
Diabetes	0.68	0.33	0.04	0.04	1.32
Hypertension	-0.21	0.27	0.44	-0.73	0.31
		Mental health			
Depression	0.31	0.38	0.41	-0.43	1.05
Stress	0.06	0.44	0.90	-0.80	0.91
		Personality			
Openness	0.00	0.00	0.98	-0.01	0.01
Neuroticism	0.00	0.00	0.42	-0.01	0.01
Conscientiousness	0.00	0.01	0.74	-0.01	0.01
Agreeableness	0.00	0.01	0.81	-0.01	0.01
Extroversion	-0.01	0.00	0.06	-0.02	0.00

Table 2.14: BMI change of individuals engaged at week 12
OLS Regression (n=852)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	2.26	0.65	0.00	0.98	3.53
Demographics					
Male	-0.12	0.13	0.35	-0.38	0.13
Age	-0.03	0.02	0.10	-0.06	0.01
Age squared	0.00	0.00	0.31	0.00	0.00
White (ethnicity)	-0.86	0.35	0.01	-1.55	-0.17
Indices of deprivation	-0.01	0.02	0.35	-0.05	0.02
Partner	-0.06	0.08	0.45	-0.22	0.10
Presence of Children	0.11	0.10	0.29	-0.09	0.31
Employed	0.04	0.09	0.67	-0.13	0.21
Degree level education	-0.24	0.10	0.01	-0.44	-0.05
Perception of local area	0.00	0.00	0.57	-0.01	0.00
Weight factors					
BMI (initial)	-0.04	0.01	0.00	-0.06	-0.02
Weight change (kg) week 2	0.27	0.02	0.00	0.23	0.30
Aspect of the programme					
Self-referred	-0.06	0.07	0.40	-0.21	0.08
Days (referral to registration)	0.00	0.00	0.40	-0.01	0.00
Days (registration to start)	-0.01	0.00	0.07	-0.02	0.00
Consistent attendance	-0.73	0.07	0.00	-0.87	-0.58
Health behaviours					
Smokes	-0.23	0.13	0.08	-0.49	0.03
Excess alcohol consumption	0.17	0.13	0.21	-0.10	0.43
Perception of diet	0.00	0.00	0.15	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.29	0.00	0.00
Physical health					
Disabled	-0.17	0.17	0.32	-0.51	0.17
Cardiovascular disease	0.10	0.14	0.45	-0.16	0.37
Mobility problems	0.07	0.09	0.41	-0.10	0.25
Diabetes	0.26	0.12	0.03	0.03	0.48
Hypertension	-0.07	0.09	0.49	-0.25	0.12
Mental health					
Depression	0.14	0.13	0.31	-0.12	0.40
Stress	0.01	0.15	0.97	-0.30	0.31
Personality					
Openness	0.00	0.00	0.99	0.00	0.00
Neuroticism	0.00	0.00	0.42	0.00	0.00
Conscientiousness	0.00	0.00	0.98	0.00	0.00
Agreeableness	0.00	0.00	0.94	0.00	0.00
Extroversion	0.00	0.00	0.12	-0.01	0.00

Table 2.15: Significant weight loss of individuals engaged at week 12
Maximum Likelihood Estimation (n=852)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	-1.14	0.88	0.20	-2.87	0.59
Demographics					
Male	-0.02	0.19	0.91	-0.39	0.35
Age	0.04	0.02	0.09	-0.01	0.09
Age squared	0.00	0.00	0.24	0.00	0.00
White (ethnicity)	0.75	0.46	0.10	-0.15	1.65
Indices of deprivation	-0.01	0.02	0.51	-0.06	0.03
Partner	0.07	0.11	0.53	-0.15	0.29
Presence of Children	-0.36	0.15	0.02	-0.65	-0.06
Employed	-0.10	0.12	0.41	-0.34	0.14
Degree level education	0.22	0.14	0.12	-0.05	0.49
Perception of local area	0.00	0.00	0.96	-0.01	0.01
Weight factors					
BMI (initial)	-0.03	0.01	0.03	-0.05	0.00
Weight change (kg) week 2	-0.26	0.03	0.00	-0.31	-0.21
Aspect of the programme					
Self-referred	0.05	0.10	0.61	-0.15	0.25
Days (referral to registration)	0.00	0.00	0.62	-0.01	0.01
Days (registration to start)	0.02	0.01	0.01	0.00	0.03
Consistent attendance	0.75	0.10	0.00	0.56	0.95
Health behaviours					
Smokes	0.15	0.19	0.43	-0.22	0.53
Excess alcohol consumption	-0.19	0.19	0.30	-0.55	0.17
Perception of diet	0.00	0.00	0.88	-0.01	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.29	0.00	0.00
Physical health					
Disabled	0.11	0.26	0.68	-0.40	0.61
Cardiovascular disease	0.00	0.19	1.00	-0.37	0.37
Mobility problems	0.11	0.12	0.37	-0.13	0.35
Diabetes	-0.42	0.16	0.01	-0.73	-0.11
Hypertension	0.14	0.13	0.30	-0.12	0.40
Mental health					
Depression	0.08	0.19	0.69	-0.29	0.44
Stress	-0.33	0.21	0.12	-0.75	0.08
Personality					
Openness	0.00	0.00	0.48	-0.01	0.00
Neuroticism	0.00	0.00	0.72	0.00	0.01
Conscientiousness	0.00	0.00	0.45	-0.01	0.00
Agreeableness	0.00	0.00	0.97	-0.01	0.01
Extroversion	0.00	0.00	0.47	0.00	0.01

2.6: Discussion

This section discusses the results of the analysis. The results are discussed in the context of previous literature. A relatively small body of evidence exists exploring the predictors of weight loss success, the results of which are summarised in Table 1.6 presented previously in Chapter 1.

As previously stated, the literature summary table from Teixeria et al. (2005) has been adapted and expanded to include further relevant research, specifically research published post-2005 and/or exploring factors beyond the psychosocial variables of interest in the original review. This literature search was limited to non-surgical, non-pharmacological weight loss programmes. Programmes aimed at children and post-partum women were also excluded. See Table 1.6.

2.6.1: Age

Data from the 2011 Health Survey for England (HSE) (Craig and Mindell, 2012) finds that obesity prevalence increases with age peaking between ages 45 to 64 for men and 65 to 74 for women. Interestingly, whilst prevalence is highest amongst the older age groups, we find that older age is associated with positive weight loss outcomes, although the marginal effect is minimal. We find a significant positive relationship between age and percentage weight loss at weeks ten and twelve. The estimated coefficients are -0.08 (p-value=0.03) and -0.10 (p-value=0.05) for week ten and twelve outcomes respectively.

Of the previous weight loss studies that consider age, findings are mixed. Handjieva-Darlenska et al. (2012) find some evidence of an association between older age and better weight loss outcomes; Elfhag and Rössner (2010) and Kong et al. (2010) find no significant effect of age; and Ortner-Hadžiabdić et al. (2014) find younger individuals lose significantly more weight in the early stages of the programme they examine, however, this effect diminishes over time.

Despite increasing the probability of successful outcomes when measured on a continuous scale (percentage weight change and BMI change), it is not associated with the achievement of the significant weight loss threshold (≥5% weight loss). Ortner-Hadžiabdić et al. (2014) and Kong et al. (2010) use this binary variable as the weight loss outcome which may explain their findings of a lack of a significant association with age.

Elfhag and Rössner (2005) suggest older individuals may benefit from stabilities such as living arrangements, employment and relationships which enable the formation of habitual healthy eating and physical activity behaviours (Stubbs et al., 2011).

2.6.2: Employment

We, however, find no association between employment and weight loss outcomes. This may be due to our use of a binary measure of employment which, whilst simple to interpret, does not provide a measure of the stability of employment which is the suggested driver of successful weight loss by Elfhag and Rössner (2005).

2.6.3: Partner

We also find no association between having a partner and weight loss outcomes. As with employment, this binary variable does not provide a measure of the stability of the relationship which may be of more importance to weight loss attempts.

Reflecting on the available literature, a systematic review by McLean et al. (2003) finds that spouse involvement seems to increase chances of successful weight loss whilst Wing et al. (1991) and Ortner-Hadžiabdić et al. (2014) find being married decreases the probability of success, thus, highlighting the complexities of the relationship between weight change and the presence of a partner.

On one hand, there is strong evidence which shows that BMIs of partners are correlated (Jeffery and Rick, 2001). Two frameworks for this relationship have been proposed; the Marital Causation Model (marriage causes BMIs of couples to align), and the Marital Selection Model (similarities in BMI increases the likelihood of becoming married) (Sobel et al., 1992). Jeffery and Rick (2001) find no evidence of the Marital Selection Model; however, they observe substantial changes in the weights of individuals who, over the study period, get married. Specifically, marriage was associated with a 0.71 increase in BMI in men ($p < 0.01$) and a 0.70 increase in BMI in women ($p < 0.04$) (Jeffery and Rick, 2001). To what extent this is related to the general increase in BMI associated with increasing age is, however, unclear.

Further and conversely, is the evidence regarding social support. Social support refers to the help individuals have available to them. Most often, social support is a self-reported measure, thus, reflecting a perception of support rather than a tangible measure of received support. There is no evidence of an association between social support and weight loss outcomes when social support is measured pre-treatment (Teixeira et al., 2005), however, higher levels of social support, measured during treatment, is associated with better weight loss outcomes (Stubbs et al., 2011). Research exploring social support and weight loss is generally concerned with the impact of the provision of group interventions compared to autonomous weight loss attempts and finds group support tends to yield better outcomes (Heshka et al., 2003). Discussions regarding perceived support provide the theoretical underpinning of the hypothesis that the presence of a partner will increase the probability of successful weight loss outcomes. Building on this hypothesis, Wing and Jeffery (1999) recruited 166 participants either alone or with 3 friends or family members and then randomly assigned them to standard treatment or standard treatment with social support strategies[18]. At a 10 month follow up only 24% of those recruited alone and with standard treatment maintained their weight loss compared to 66% of individuals recruited with friends and family and given standard treatment with social support. The effect of having a partner on weight loss will be highly dependent on the type and level of support they provide. Williams et al. (1996) found, for example, that weight loss was more probable in participants who perceived healthcare staff to be more 'autonomy-supportive' (defined as support which facilitated self-determined and self-motivated behaviour change) compared to more controlling and instructional approaches. Further, Gorin et al. (2005) found that individuals recruited in groups to a physical activity based weight loss programme were only more likely to lose weight if other members of the group also did so. The complexities of social support may, therefore, account for the lack of association found in our analyses.

[18] Social support strategies included intra-group team building activities and intra-group competitions.

2.6.4: Presence of children

One form of social support explored in the literature is the effect of parental involvement on weight loss in children. McLean et al. (2003), for example, finds strong evidence that higher involvement from parents increases the probability of successful weight loss in children but suggests this is not the case for adolescents.

The reverse relationship (i.e. the effect of children on parental weight loss) has received limited exploration. One study, by Gripeteg et al. (2010), finds, in women, greater weight loss was predicted by having more children. One hypothesis is that children may provide a form of social support to parents attempting to lose weight, particularly if the child is also attempting weight loss or has the capacity to share skills and strategies for success. This hypothesis is based on the same theoretical underpinning of the effect of the involvement of partners and is most likely to be true in individuals with older children. A recent study by Coffield et al. (2015), however, found modest but significant weight loss in parents of children aged 6 to 10 who were enrolled in a community healthy weight programme, suggesting activities of younger children may also be impactful on the behaviour change of parents.

A second hypothesis is that the presence of children may offer parents an increased incentive for weight loss and better care of health more generally.

Interestingly, we find having children to be negatively associated with the probability of achieving a significant weight loss at week twelve. The estimated coefficient is -0.36 (p-value=0.02).

One hypothesis is that dietary alterations and behaviour changes required by the weight management service for successful weight loss may be more difficult to achieve with children due to lack of time and/or the inability of individuals to align new behaviours and dietary habits within the family domain.

A further suggestion is, for women, pregnancy and childbirth is associated with an increased risk of the onset of obesity (NICE, 2010) and may also cause longer-term physiological changes resulting in difficulties achieving weight loss. We do not collect information on the age of children and, thus, cannot make an assessment on the likelihood of the postpartum effect on weight loss.

2.6.5: Physical Health

An interesting aspect of the previous discussion regards the concept of attributes which provide individuals with additional incentives to lose weight. Whilst children have been previously suggested, another attribute may be the presence of a health condition which can, to some extent, be alleviated through weight loss.

This hypothesis is theoretically underpinned by the Health Belief Model (Janz and Becker, 1984). The Health Belief Model is one of the thirty-three theories upon which the COM-B model of behaviour change was built. The Health Belief Model proposes that behaviour is determined by six key concepts; perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action and self-efficacy. It is hypothesised that the presence of a health condition may increase the perceived severity of obesity and the perceived benefits of weight loss. Further, in its early stages the development of a health condition may provide a “cue to action”.

This hypothesis is explored through the analyses of the effect of being disabled or having diabetes, CVD, mobility co-morbidities or hypertension on weight loss outcomes. The general health of individuals with these conditions has been shown to benefit from weight loss, thus, potentially providing increased motivation for success.

Contrary to these expectations, diabetic individuals experienced significantly worse weight outcomes at week twelve compared to their non-diabetic counterparts. Percentage weight change and BMI change were positively associated with diabetes and significant weight loss was negatively associated with diabetes. Coefficients are 0.67 (p-value= 0.04), 0.26 (p-value =0.03) and -0.42 (p-value =0.01) respectively. Further, individuals with CVD experienced significantly worse outcomes at week twelve with respect to BMI change. The estimated coefficient is 0.44 (p-value0.01). No associations were found between weight loss outcomes and the other three co-morbidities.

Obesity is a significant risk factor for both the development of type-2 diabetes and the risk of complications associated with diabetes (PHE, 2014). Weight management can play a critical role in reducing the probability of diabetic complications. The findings of this analysis warrant further research to understand why the programme seems to be less successful for diabetics and what can be improved to meet this need.

The insignificant relationships between physical health factors and weight loss are, however, encouraging, as they suggest individuals with these conditions are as successful as their non-disabled counterparts.

2.6.6: Education

Elfhag and Rössner (2005) propose that as age increases individuals may become efficient at developing coping and behaviour management strategies which support weight loss efforts, whereas, younger individuals may have not had time to develop such skills (Stubbs et al., 2011). Based on this hypothesis that successful weight loss is supported by an individual's ability to effectively reflect, evaluate and develop strategies, it is understandable how one may hypothesise, not only a positive relationship between weight loss success and age, but also between weight loss success and education.

Indeed, a substantial body of evidence exists documenting the persistent positive relationship between education and health generally (Cutler and Lleras-Muney, 2006). In their comprehensive paper, Cutler and Lleras-Muney (2006) advocate the hypothesis that higher education increases both access to information but also the ability to effectively process information through refined critical thinking skills and decision-making abilities (Cutler and Lleras-Muney, 2006). In the context of weight management this may present as efficiency in understanding and applying dietary and behavioural modifications conducive to weight loss.

The 2011 HSE (Craig and Mindell, 2012) provides evidence of an association between education and static weight status, finding a negative association between education and obesity prevalence. As education attainment increases the prevalence of obesity decreases, with individuals educated to degree level or higher experiencing the lowest prevalence (21% for men and 18% for women) compared to individuals with no qualifications experiencing the highest prevalence (30% for men and 33% for women) (NOO, 2014). The 2011 HSE (Craig and Mindell, 2012) concludes that education may serve as a protective factor against initial weight gain.

We find being educated to degree level or higher is associated with positive weight loss outcomes for individuals who do become obese. Specifically, degree level education is associated with greater percentage weight loss at weeks ten (β=-0.73, p-value=<0.01) and twelve (β=-0.73, p-value=0.01) and greater decrease in BMI at week twelve (β=-0.24, p-value=0.01).

Little attention has been given to education as a predictive variable. Two studies (Ortner-Hadžiabdić et al., 2014 and Karlsen, Søhagen and Hjelmasæth (2013)) find no significant associations between weight loss and education. Below are three possible explanations for the differing result.

(1) We find an association between education and the variables "weight change" and "BMI change". Despite increasing the probability of weight loss when measured on these continuous scales, we find no association between education and the binary variable; achievement of ≥5% weight loss. The outcome variable examined by Ortner-Hadžiabdić et al. (2014) is this binary measure and, thus, may explain why they do not find a significant association with education but we do.

(2) The study by Karlsen, Søhagen and Hjelmasæth (2013) differs in its definition of education. They use a categorical variable years of education (<9 years, 9-12 years and >12 years) which whilst being a common approach is an assessment of duration of education rather than a direct measure of educational attainment. We previously discuss the limited comparability of studies due to the heterogeneity of definitions of the predictor variables, potentially accounting for the differing results in the analyses.

(3) Our study reports weight loss outcomes at 10 and 12 weeks, whereas, both Karlsen, Søhagen and Hjelmasæth's (2013) and Ortner-Hadžiabdić et al.'s (2014) report weight loss outcomes over a much greater time frame of 1 year. If more educated individuals experience more successful weight loss outcomes due to a relative immediate efficiency in behaviour modification it may be possible that over time this relationship will diminish. This theory relies on the assumption that less educated individuals have the capacity to successfully change behaviour they just take longer to do so.

Aitsi-Selmi et al. (2013) further discussions regarding the relationship between education and obesity. They propose that within a wider environment, having a higher level of education may assist in correcting cognitive biases created in the external environment, for example, the relative ease of physically inactive transportation and the availability of unhealthy foods. They hypothesise that individual's draw on "personal resources such as educational capital and cognitive skills" to counter the influential nature of the "increasingly obesogenic environment" and modify behaviours to reflect more healthy decisions.

2.6.7: Perception of Local Area

The influential nature of the external environment has previously been introduced in Section 2.2 as a key recommendation for future studies (Stubbs et al., 2011). Further, in Appendix 10 we outline how perceptions of local areas were collected as an assessment of the influence of the obesogenic environment i.e. the influence of the external environment on weight.

Surprisingly, we find no association between perception of local area and weight loss outcomes.

An individual's perception of the extent to which the local environment encourages obesity is related to a very interesting area of research exploring associations between weight loss and locus of control, where locus of control refers to the extent to which individuals believe they can control events affecting them. Obese individuals who perceive externalities, rather than their own behaviours, to be largely responsible for their weight status may be more likely to perceive their local area to be an obesogenic environment (Lazzeretti et al., 2015).

Within the current literature, Allison and Engel (1995) and Nir and Neumann (1995) both find evidence of an association between high internal locus of control (i.e. an individual's belief that their weight status largely depends on their own behaviours) and positive weight outcomes. In a more recent study, Wiltink et al. (2007) found an association between individuals who recognised and attributed weight status to dietary behaviour and long term relative weight loss success.

2.6.8: Personality

Research exploring locus of control is highly related to research exploring the predictive nature of broader personality traits on weight loss. Past literature (summarised by Teixeira et al (2005 and Stubbs et al., 2011) finds a consistent lack of association between personality and weight loss outcomes. The past literature has, however, received noteworthy criticism for the use of the Karolinska Scales of Personality (KSP)[19] methodology to measure personality. Lazzeretti et al. (2015) question the suitability of the KSP due to its origins as an assessment method for abnormal personality, rather than variations in normal personalities (Lazzeretti et al., 2015).

Despite using a more appropriate methodology (BFI), we too, find no association between measures of personality and weight loss outcomes.

This is an interesting finding considering Atherton et al.'s (2014) recent large scale study (n=460,127) of weight status and personality using the BFI. The analyses found conscientiousness to be a robust predictor of weight status with conscientious individuals having 40% lower odds of being obese (Atherton et al., 2014). Further, although a pharmacological study, it is worth mentioning the findings of Elfhag and Rössner (2008) who observed an association between contentiousness and higher weight loss in participants receiving Orlistat (an obesity treatment drug).

[19] KSP measures the personality with a 135 item questionnaire with answers on a four point Likert scale. The answers are grouped into 15 scales: Psychic anxiety, Somatic anxiety, Muscular tension, Psychasthenia, Inhibition of aggression, Detachment, Impulsiveness, Monotony avoidance, Socialization, Indirect aggression, Verbal aggression, Irritability, Suspicion, Guilt and Social desirability (Ortet et al., 2002).

Individuals scoring high on the measure of contentiousness are characterised as self-disciplined, task oriented and well organised (Lazzeretti et al., 2015). This finding is reflected in research exploring coping strategies and weight loss outcomes. Kayman, Bruvold, and Stern (1990), for example, find more successful weight outcomes in individuals confronting problems directly rather than those resorting to emotion-focused coping strategies (such as comfort eating).

2.6.9: Deprivation

The research regarding coping strategies and response to problem solving is pertinent to hypotheses regarding the predictive nature of deprivation on weight loss outcomes. McLeod and Kessler (1990), for example, report that less deprived individuals often exert a more educated and less emotional response to negative life events. As previously discussed, whilst the literature is limited, it suggests this personal attribute may be important to successful weight loss and seemingly may also lack among individuals of a lower socioeconomic status (McLeod and Kessler, 1990).

Sometimes referred to as “societal rank”, there is strong evidence of a relationship between deprivation and ill health (Marmot, 2002) and, specifically, between deprivation and obesity status (NOO, 2014). The causal relationship is complex; however, a substantial quantity of evidence exists suggesting that one’s rank in society may have consequences for health (Marmot, 2002).

As deprivation is a construct of variables such as employment, education and, to some extent, the immediate environment an individual resides in (see Appendix 10); several of the discussions presented so far provide the foundations of the theory supporting a hypothesised association between deprivation and weight loss. One such hypothesis is that a relationship exists because individuals at the lower end of the societal hierarchy have comparably less perceived and actual control over their lives which has been shown to cause increases in stress and stress-related diseases such as obesity (Cutler and Lleras-Muney, 2006). This hypothesis relies heavily on the theory of locus of control, explored previously.

Given the strength of the evidence, a relatively surprising observation, therefore, is that we find no association between deprivation and weight loss. Although surprising, this finding does, however, support the previous discussion of the need for specific research into weight loss rather than a reliance on assumptions that factors associated with static weight status and weight change are the same.

2.6.10: Mental Health

A significant aspect of the previous discussion is the suggested importance of individual's mental health on their physical health. There are continuing debates in the literature regarding the causal relationship between common mental health conditions and obesity. Whilst some hypothesise that mental health conditions cause individuals to become obese, an equal number believe the opposite to be true i.e. that obesity causes mental health conditions to develop (Gatineau and Dent, 2011).

Luppino et al. (2010) conducted a systematic review and meta-analysis of the longitudinal relationship between obesity and depression in an attempt to reduce the ambiguity regarding the association between the two variables. Whilst the verdict of a reciprocal relationship between depression and obesity is unsurprising, the authors quantify the magnitude of each of the proposed causal relationships concluding that; obesity will increase the risk of developing depression by 55% over time, whereas, depression will increase an individual's risk of obesity by 58%.

This bidirectional relationship and non-static nature of depression and obesity potentially explain the lack of significant findings, both in our analyses and in the wider literature (Teixeira et al, 2005 and Stubbs et al., 2011). Pre-treatment baseline assessments of depression may fail to fully examine the complexity of the relationship between the variables.

The relationship between stress and obesity is under-researched and, therefore, not well understood. Higher levels of stress have been seen to correlate with obesity related behaviours such as poor diet and lack of physical activity (Ng and Jeffery, 2003). Further, treatments for obesity often incorporate stress management activities (Teixeira et al., 2005) signalling an anecdotal belief of a relationship between these variables. As with depression, longitudinal variations in stress may render pre-treatment baseline assessments of the condition unsuitable and, thus, further bespoke research may be required.

A well-established symptom of these common mental health conditions is lack of motivation and general low self-esteem. Often, research has concentrated on the impact of weight loss on self-esteem, finding a positive relationship (Lazzetti et al., 2015). Indeed, in a follow up survey to our research, 79% of respondents (n=208) agreed that they felt more self-confident as a result of the programme (see Appendix 11). The reverse relationship of pre-existing self-esteem on subsequent weight loss is less understood. One study, however, concludes that self-esteem may be related to obesity related behaviours in women (Daniali et al., 2013).

The research on self-motivation is relatively more substantial, finding a consistent positive relationship i.e. higher self-motivation is associated with more successful weight outcomes (Teixeira et al., 2004). As previously discussed (see Section 2.4.3.2), we collect information regarding the referral route, requiring referrers to indicate whether the individual instigated the referral. Arguably, self-referral is a good proxy for self-motivation and, to some extent, internal locus of control (evidence of a belief that their weight status largely depends on their own behaviours), thus, we hypothesise that self-referred individuals will exhibit more successful weight loss outcomes than those who are referred by external recommendation.

2.6.11: Self-Referral

Looking to the analyses, individuals who self-refer are significantly more likely to achieve greater percentage weight loss at week ten. The coefficient is -0.31 (p-value=0.05). Further, whilst not strictly with the 5% significance level (p-value=0.06) the coefficient for self-referral on significant weight loss at week 10 is also worth reporting; 0.17.

No previous literature has specifically explored referral type as a factor associated with weight outcomes. A paper by Gorin et al. (2004) exploring triggers of weight loss is, however, worth discussing. Gorin et al. (2004) uses the National Weight Control Registry (NWCR) to examine self-reported reasons for weight loss. Reasons for weight loss were grouped into medical (n=207)[20], non-medical (n=539)[21] and no-trigger (n=171). In our study, the alternative to self-referral is a referral recommended by a health professional. Whilst not directly comparable, this alternative is broadly similar to Gorin's definitions of a medical trigger for weight loss. In contrast to our findings, however, Gorin et al. (2004) find that medical triggers (i.e. non self-referral) are associated with greater weight loss at year 1 and year 2.

One possible explanation for the differing findings is Gorin et al.'s (2004) reliance on self-reported weight and self-reported triggers of weight loss which were collected at least 1 year post weight loss. The time delay in reporting triggers may alter perceptions on past motivations on weight loss. Further, the sample used by Gorin et al. (2004) is extracted from the NWCR. This registry is limited to individuals who lose a minimum of 30lbs and maintain this loss for at least 1 year, thus, sample selection is likely to bias results.

2.6.12: Consistent Attendance

Another aspect of the programme we explore is consistency of attendance. Amongst the current literature, attendance has been robustly established as one of the most consistent correlates of weight loss (Stubbs et al., 2011). Hollis et al. (2008), for example, find a positive association between attendance and absolute weight loss, Sacks et al. (2009) report an average 0.2kg loss for every session attended and Karlsen, Søhagen and Hjelmasæth (2013) find a positive association between the frequencies of GP visits and mean excess weight loss.

[20] Medical triggers are defined as "medical recommendation" or "health related incident".
[21] Non-medical reasons defined as "emotional", "lifestyle", "external inspiration or impetus", "availability of services", "self-perception" and "weight/size reached lifetime high".

Whilst, research on frequency of attendance is of value, more interesting and, arguably, pertinent, is the exploration into the pattern of attendance. We, therefore, explore the binary variable of consistent attendance, where; consistent attendance indicates no periods of absence prior to drop out (see previous discussions for a full definition).

The result of the analyses find individuals who consistently attend achieve greater percentage weight loss at weeks ten (β=-1.59, p-value=<0.01) and twelve (β=-1.98, p-value=<0.01), greater decreases in BMI at weeks ten (β=-0.62, p-value=<0.01) and twelve (β=-0.73, p-value=<0.01) and are more likely to achieve significant weight loss at weeks ten (β=0.61, p-value=<0.01) and twelve (β=0.75, p-value=<=0.01). The coefficients in the analyses of the continuous variables (weight change and BMI change) are particularly sizable. There are two main theories regarding this relationship between consistency of attendance and weight loss outcome.

(1) Attendance increases the likelihood of weight loss success i.e. increasing exposure to the service subsequently increases the probability of higher weight loss.

(2) Both attendance and weight loss are a product of a third factor; pre-existing motivation. Low motivation at the initial stage of the programme may continue throughout the service resulting in both inconsistent attendance and poor weight loss outcomes.

In the following Chapter we examine the relationship of consistent attendance with overall attendance to perhaps shed some light on these hypotheses.

Individuals with a higher frequency and consistency of attendance will also be exposed to a higher frequency of formal monitoring of their weight. Thus, the literature exploring the effect of frequency of monitoring weight on overall weight outcomes is of particular interest. In their systematic review, Burke, Wang and Sevick (2011) found a consistent positive association between monitoring activities and weight loss. Of most interest to our study are the six studies[22] considering frequency of weighing oneself on weight loss (other monitoring activities of less interest included completion of food and/or exercise diaries). Taking advantage of a large sample (n=1,800), Linde et al. (2005) conclude that daily weighing is a valuable activity for individuals attempting to lose weight. Whilst assessing a relatively small sample (n=100) VanWormer et al. (2009) quantifies the relationship between weight monitoring and weight loss finding that, individuals lost “1 extra pound for every 11 days they self-weighed”.

The structure of the service observed in this thesis consists of weekly meeting and weight measurements. Interestingly, individuals are discouraged from interim self-monitoring of weight but are encouraged to engage in other monitoring activities, such as food records. Given the recommendations in the literature, an interesting extension to this research would be to assess the effect of various frequencies of weight monitoring with the objective to assess whether the current discouragement of interim weight monitoring is appropriate.

Of particular importance in the discussion regarding consistent attendance and weight loss is the issue of endogeneity. Endogeneity occurs when an explanatory variable is correlated

[22] Butryn et al. (2007), Gokee-LaRose et al. (2009), VanWarmer et al. (2009), Welsh et al. (2009), Linde et al. (2005) and Wing et al. (2006).

with the error term (Wooldridge, 2009). Two common causes of endogeneity are (1) an uncontrolled confounder which causes both the independent and dependent variables and (2) a loop of causality between the independent and dependent variables (Wooldridge, 2009).

In the current context endogeneity may arise as an issue due to the looped causality between the independent variable (consistent attendance) and the dependent variable (weight loss). We previously discuss the hypothesised effect of attendance on weight loss, however, one can equally envisage the effect weight loss may have on attendance, for example, the desire to evidence social conformity when weight loss is achieved resulting in attendance at a subsequent session. Pertinent to discussions is the literature which explores, theoretically and empirically, the sequential nature of behaviours in pursuit of a goal and the effect prior behaviour has on present behaviour (Laran and Janiszewski, 2009). In the current case, the effect attendance has on weight loss behaviour and subsequently the effect of the behaviour on future attendance.

This problem of looped causality has been highlighted previously as an issue with research concerning weight loss (Norton and Han, 2008). A suggested correction for this issue is the introduction of an instrumental variable into regression models (Wooldridge, 2009). An instrumental variable takes the form of a variable that can only affect the dependent variable through the independent variable in question i.e. it induces instrumental change in the independent variable and should have no partial effect on the dependent variable after the independent variable is controlled for (Wooldridge, 2009). In the current context identification of a suitable instrumental variable is difficult due to the integrative nature and complexity of the variables examined. One may assume that distance from an individual's home to the weight management group, for example, could have been used. Due to the geographical prevalence of groups, however, one may easily hypothesise that increased distance from a group may also reflect increased distance from food environments and physical activity opportunities which will directly affect weight loss. Whilst this is one only one example it demonstrates the difficulties of instrumental variable identification with a complex system such as obesity. Further, due to the nature of the research (i.e. field research) the collection of variables was constrained by the practically of service delivery. There were limited opportunities to introduce new variables and, thus, unless instrumental variables were collected automatically within existing systems the introduction into the models presented is difficult.

The choice is, therefore, between omitting variables with strong theoretical and, often, empirical support (which of course leads to other estimation issues) or to acknowledge and account for the consequences of endogeneity. A limitation of our study is that endogeneity is not specifically controlled for; however, through this acknowledgement we are able to carefully interpret and discuss results. Firstly, in the context of consistent attendance we acknowledge the inability to determine causation and to this effect do not interpret results or come to conclusions which rely on such assumptions. The main objective of the research is to provide evidence for the continuous improvement of weight management services, thus, in the current context simply providing evidence of a relationship between consistent attendance and weight loss allows providers to identify individuals who miss session and provide tailored support to increase probability of weight loss success.

Before continuing with the discussions of the individual variables, it is acknowledged that the issue of endogeneity is not unique to the relationship between consistent attendance and weight loss. As made clear by the Foresight Map (see Figure 1.1) the factors associated with weight loss are complex, interrelated and causation is often multidirectional and looped. From an analytical perspective this is, unfortunately, the nature of the issue, however, where possible attempts have been made to recognise the limitations of endogeneity and results of analyses have been interpreted cautiously.

2.6.13: Time

A further aspect of the programme explored in our analyses is time, specifically the length of time between stages of the programme. A plethora of evidence regarding time from referral to treatment is available in the wider health literature. The majority of this literature concerns conditions in which delays to treatment may result in irreversible poor health, delays to cancer treatment, for example. Detriment to physical health is less applicable when considering the time between referral and treatment of obesity. What is of greater concern is impact of time on psychological factors such as motivation and readiness-to-change.

It is hypothesised that individuals who take longer to register and/or start the service will experience less successful weight outcomes. Similar to the variable “attendance”, two differing theories support this hypothesis.

(1) Motivation to change is greatest at referral and decreases with time, thus, the longer the period of time between referral and treatment, the lower the probability of successful weight loss.

(2) Motivation is stable across time. Times between stages of the programme and weight loss are products of pre-existing motivation. Low motivation results in both an increased period of time to the start of treatment and also poor weight loss outcomes.

Looking to the analyses we, surprisingly, observe the opposite relationship. Greater time between registration and starting is associated with better weight loss outcomes. Specifically significant weight loss (β=0.01, p-value=0.03) and BMI change (β=-0.01, p-value=0.05) at week ten and greater percentage weight loss (β=-0.02, p-value=0.05) and significant weight loss (β =0.02, p-value=0.01) at week twelve.

One explanation for these findings is; the assumption that motivation is greatest at referral (hypothesis 1) and decreases over time may be incorrect. If we accept motivation levels may vary over time, we must also consider that motivation may increase over time or that the relationship between motivation and time may be non-linear.

Whilst pre-treatment measures of motivation consistently predict weight loss success (see previous discussion), changes in motivation over time have not been systematically investigated (Teixeira et al. 2012). A popular theoretical model of the stages of change, the

Transtheorectical Model[23] (Prochaska and Veliser, 1997), is often criticised for its overly simplistic linear structure i.e. individuals do not move neatly from stage-to-stage finally terminating once a behavioural goal is reached. This would support the notion of non-linear motivation over time. Indeed, Webber et al. (2010) investigates the shape of the relationship between motivation over time and weight loss and evidences motivation to vary non-linearly. We observed an average time between registration and starting of 13 days. Webber et al. (2010), however, measure motivation at four weekly intervals, proving little insights as to how motivation may vary across a shorter time period. Further, motivation is measured across treatment and maintenance of weight, whereas we are interested in motivation pre-treatment.

Motivation to change, whether conscious and reflective or unconscious and automatic, is important to understand when considering predictors of successful weight loss (Teixeira et al., 2012). Recommended further research include an exploration, and potentially modelling, of how motivation varies over a weight loss attempt and in response to stimuli throughout a weight management programme.

2.6.14: Initial Weight Loss

The theory of the effect of motivation on weight loss is also pertinent to discussion regarding the association between initial weight loss and overall weight loss outcomes.

The available literature suggests that initial or early weight loss is a consistent predictor of success (Johnston, 2013) with several studies concluding that greater initial weight loss is

[23] The transtheoretical model states that health behaviour change involves progress through six stages of change: pre-contemplation, contemplation, preparation, action, maintenance, and termination.

associated with successful longer-term outcomes (Ortner-Hadžiabdić et al., 2014; Fabricatore et al., 2009; Elfhag and Rössner, 2010; Handjieva-Darlenska et al., 2012, 2012; Karlsen, Søhagen and Hjelmasæth, 2013; Wadden et al., 1992; Kong et al., 2010).

The definition of initial or early weight loss varies quite considerably between studies (see Table 2.16). At one extreme Karlsen, Søhagen and Hjelmasæth (2013) define early weight loss as outcomes at week 12 as a predictor of weight loss at 1 year. At the other end of the spectrum, and a closer reflection of the parameters of our study, Handjieva-Darlenska et al. (2012) defines initial weight loss as outcomes at week 1 as a predictor of weight loss at week 10.

Reference	Timescale of initial or early weight loss	Timescale of longer term weight loss
Ortner-Hadžiabdić et al. (2014)	1 month	1 year
Fabricatore et al. (2009)	4 weeks	1 year
Elfhag and Rössner (2010)	5 weeks	9 months
Handjieva-Darlenska et al. (2011)	3 and 8 weeks	6 months
Handjieva-Darlenska et al. (2012)	1 and 5 weeks	10 weeks
Karlsen, Søhagen and Hjelmasæth (2013)	12 weeks	1 year
Wadden et al. (1992)	4 weeks	6 months and 1 year
Kong et al. (2010)	6 weeks	1 year

Table 2.16: Definitions of initial or early weight loss

Interestingly, regardless of how the variables are defined it seems that higher early weight loss significantly increases the probability of successful longer term weight outcomes.

This research supports these findings, observing greater initial weight loss, defined as weight loss at week two, is associated with higher percentage weight loss ($\beta=0.63$, p-value=<0.01), greater reductions to BMI ($\beta=0.23$, p-value=<0.01) and significant weight loss ($\beta=-0.25$, p-value=<0.01) at week ten and higher percentage weight loss ($\beta=0.71$, p-value=<0.01), greater reductions to BMI ($\beta=0.27$, p-value=<0.01) and significant weight loss at week twelve ($\beta=-0.26$, p-value=<0.01).

The theoretical underpinning of the relationship between initial and longer term weight loss is not well understood. As with the variable “time”, two hypotheses exist.

(1) Initial weight loss increases motivation for subsequent positive behaviour resulting in better overall weight loss outcomes.

(2) Initial weight loss and overall weight loss are both products of pre-existing motivation. Lower motivation leads to both poor initial weight outcomes and poor overall weight loss outcomes.

Initial weight loss as a motivating factor for subsequent positive behaviour may be linked to the literature regarding the relationship between weight loss expectations and outcomes. Setting weight loss expectations has become standard practice in most weight management interventions (Powell, Calvin and Calvin, 2007). The impact of this activity is not, however, widely studied yet the implications of inappropriate expectations may be detrimental (Stubbs et al., 2011). In their review of the literature, Teixeria et al. (2005) conclude that, generally, individuals with positive but moderate weight loss expectations (neither minimal nor demanding expectations) achieve more successful weight loss outcomes. Conversely (and somewhat controversially), Elfhag and Rössner (2005) suggest unrealistic weight outcomes can be healthy and encourage greater achievements.

All previous studies exploring the association of initial weight have controlled for baseline weight by exploring initial percentage weight change. In this analysis, however, absolute weight change (kg) at week two is used. Assuming initial weight loss determines motivation for subsequent behaviour, the measure of initial weight loss should reflect the information individuals receive. Within the weight management service, absolute weight change is communicated to individuals. Further, Slimming World have adopted a reward system (such as social acknowledgement and certificates of achievement) based on reaching absolute change milestones (e.g. 1 stone, 1 ½ stone etc.), thus, justifying the use of absolute weight change within our analyses.

An interesting extension to this research would be a specific investigation into the effects of percentage vs. absolute weight change and would complement existing behavioural research exploring the effective framing of health communications (e.g. Gallagher & John A. Updegraff, 2012).

2.6.15: Gender

Initial weight loss may partly explain why previous literature has found a significant association between gender and weight loss outcomes, with males more likely to lose more weight than women (Stubbs et al., 2011). Further clarification on this association is provided by Ortner-Hadžiabdić et al. (2014). They find males are more likely to see significant weight loss at 1 month; however, this association is not present at 12 months suggesting that due to differences in metabolism, males have an increased propensity to lose more weight in the short term but the association between gender and weight loss diminishes over time. This hypothesis is supported by the current literature. We find that studies measuring weight change in the relatively short term[24] do find significant associations between gender and weight loss, whereas literature measuring weight change in the longer term find no evidence of this association[25].

Another explanation may be due to sample selection. Several factors may result in individuals self-excluding from weight management programmes. They may, for example, lack self-motivation (see previous discussions) or perceive the risk of obesity to be low (see previous discussion regarding the Health Belief Model). Gender distribution in the wider population is approximately equal and the prevalence of obesity in males and females is relatively similar (see previous discussions), thus, we can reasonable assume similar levels of demand for weight management services. This, however, is not the case as only 10% of our sample is male. This female dominance of samples is observed consistently within weight loss research. Looking at the past literature, summarised in Table 1.6, we find just under half

[24] Examples of short term weight outcome examples include Handjieva-Darlenska et al. (2012) and Sartorio et al. (2005) who explore weight outcomes at 10 weeks and 3 weeks respectively.
[25] Examples of longer term weight outcome examples include Karlsen, Søhagen and Hjelmasæth (2013) and and Fabricatore et al. (2009) who both explore weight outcomes at 1 year.

of the studies have no male participants with very few analysing samples with a 15% or greater proportion of males. We hypothesise that the male individuals who engage in weight management activities represent a sub population of males most likely to succeed (i.e. high self-motivation, high perception of risk etc.) and, thus, exhibit better weight outcomes compared to female individuals.

Despite strong theoretical and empirical evidence for an association between weight loss and gender, we find no association between these variables.

A possible explanation for this finding is our choice of outcome variables (percentage weight loss, BMI change and significant weight loss). Many past studies have examined absolute weight change, whereas we chose to examine proportionate weight change. Absolute weight is not a true reflection of weight status as it does not account for individual's height. To clarify Table 2.17 presents the average weight (kg) and BMI at time of referral, for male and females, engaged at week twelve of the service. We use t-tests to check for significant differences between these means.

	BMI mean (SD)	p-value	Weight (kg) mean (SD)	p-value
Male	36.2 (4.9)	0.25	112.8 (17.8)	0.00
Female	35.6 (5.4)		93.8 (15.6)	

Table 2.17: Weight (kg) and BMI at referral of individuals engaged at week 12

Due to a tendency for males to be taller, we find whilst average BMIs of males and females are not statistically different from one another (36.2 and 35.6 respectively, p-value=0.25), average absolute weights (kg) are, at the <1% significance level (112.8kg and 93.8kg respectively, p-value=<0.01).

Comparing absolute weight change in males and females may, therefore, be misleading as males tend to lose more absolute weight despite both genders experiencing similar proportionate weight loss. A recommendation for weight management service is, thus, the consideration of the communication of outcomes to participants to reflect both absolute and proportional weight loss achievement.

2.6.16: Initial BMI

The Health Belief Model provides the theoretical foundations for a hypothesised association between initial BMI and weight loss. Firstly, a higher BMI may increase an individual's perception of the severity of obesity as the risk of developing co-morbidities increases with weight. Within our sample, non-diabetic individuals have an initial BMI (i.e. BMI at time of referral) of 35.4 whereas diabetic individuals have an average BMI of 37.4. A t-test reveals the difference between means is statistically significant (p-value=<0.01). Secondly, higher BMI may increase the perceived benefits of losing weight, in the alleviation or avoidance of co-morbidities. Thirdly, evidence suggests initial BMI may act as a prompt for weight loss. In Gorin et al. (2004) study of the triggers of weight loss; "*reached a lifetime high weight or clothing size*" was the most frequently reported non-medical trigger for weight loss with 21% of individuals declaring this reason. Within the Health Belief Model "cue to action" is an integral component of behaviour change providing theoretical support for this hypothesis that initial BMI may provide a trigger for subsequent successful weight loss.

Past reviews of the literature regarding initial BMI and weight loss have generally concluded a positive relationship between the variables i.e. a higher initial BMI is associated with greater weight loss (Teixeira et al., 2005 and Stubbs et al., 2011). The literature is, however, far from consistent.

An intriguing issue arises in the evaluation of the past literature. Firstly Teixeira et al. (2005) report that significant positive associations tend to be found in studies where initial BMI is high (circa ~37), where studies finding negative or no associations tend to be found in studies where initial BMI is much lower (circa ~31). They conclude that initial weight must first exceed a threshold before a significant association will be observed. Stubbs et al. (2011) find the same pattern in the studies, however, come to a different conclusion. They suggest that positive associations are due the more intensive treatments individuals with higher BMIs receive, thus, resulting in the observed increased probability of weight loss success.

We observe a complex relationship between initial BMI and weight loss. Greater initial BMI is found to decrease probabilities of successful percentage weight loss and significant weight loss at weeks 10 and 12. The coefficients are however minimal; 0.05 (p-value=0.01), 0.07 (p-value=0.01), -0.03 (p-value=0.01) and -0.03 (p-value=0.03) respectively.

On the other hand, greater initial BMI is found to increase the probability of greater BMI change at weeks 10 and 12. The coefficients are, again, minimal; -0.04 (p-value=<0.01) and -0.04 (p-value=<0.01).

Due to the formula for calculating BMI, it requires the same absolute weight loss to lose 1 BMI unit for any initial BMI, when holding height constant. For example an individual with a height of 1.64m and an initial BMI of 35 would need to lose 2.69kg to achieve a one unit decrease in BMI i.e. a BMI of 34. Holding height constant at 1.64m, an individual with an initial BMI of 30 would also need to lose 2.69kg to achieve a one unit decrease in BMI i.e. a BMI of 29. Due to several factors[26], individuals with higher initial BMIs will often experience greater absolute weight change and, thus, a greater BMI change, as found in our analyses.

Due to the calculation of percentage weight change, greater absolute weight loss is required by individuals with a higher initial BMI, to lose one percentage point of initial body weight, when holding height constant. For example an individual with a height of 1.64m and an initial BMI of 35 would need to lose 2.82kg to achieve a 1% decrease in initial weight. Holding height constant at 1.64m, an individual with an initial BMI of 30 would only need to lose 2.42kg to achieve a 1% decrease in initial weight. As such, individuals with a higher initial BMI, may struggle achieve the absolute weight loss required to equal or surpass the percentage weight loss outcomes of individuals with a lower initial BMI.

To provide further clarity, Table 2.18 outlines hypothetical weight outcomes for the two individuals described above. Individual 1 (higher initial BMI) loses more absolute weight than individual 2 (2.82kg vs. 2.69kg), thus, achieving a higher decrease in BMI (1.05 vs. 1.00). Despite individual 1's larger absolute weight change, individual 2 achieves a greater percentage change weight change (3.33% vs. 3.00%). Whilst the differences between

[26] Factors include difference in metabolism, physiological factors (i.e. more excess to lose) and treatment factors (i.e. those with higher BMIs are most likely to benefit from the behaviour changes of programmes).

outcomes are small this is reflected in the minimal marginal effects detected in our analyses.

Individual	Initial BMI	Weight (kg)	Height^2	Change (kg)	BMI change	% Weight Change
1	35.00	94.15	2.69	-2.82	-1.05	-3.00%
2	30.00	80.70	2.69	-2.69	-1.00	-3.33%

Table 2.18: Hypothetical weight outcomes of individuals with differing initial BMIs

Coming to a conclusion regarding the effect of initial weight loss of weight outcomes will depend largely on which outcome is deemed to be most important. Past literature most often cites proportionate weight change, rather than absolute weight change, as the important factor for longer term health benefits (Blackburn, 1995 and NIH, 1998[27]). As such we must conclude that initial BMI decreases the probability of weight loss success, where weight loss outcomes are reflective of the probability of long term benefits to health.

2.6.17: Health Behaviours

Returning to earlier discussion regarding deprivation it was suggested that unhealthy behaviours and poor health may cluster among more deprived individuals. The following discussions consider four further health behaviours (smoking, alcohol consumption, diet and physical activity), why they may cluster and their association with weight loss.

[27] These papers recommend a 5-10% loss of initial body weight to achieve long term reduction in the probability of co-morbidities. This recommendation has been adopted globally for the treatment of obesity.

Inconsistencies in individual's time preferences provide one theoretical foundation for why unhealthy behaviours may cluster together. The health behaviours discussed in this section all involves a trade-offs between personal gratifications from unhealthy lifestyles in the short term that lead to uncertain negative health effects in the longer term. Individuals with high discount rates may, therefore, be more likely to engage in present unhealthy behaviours such as smoking, alcohol consumption, poor dietary behaviour and lack of physical activity. Further, it is hypothesised that a hyperbolic discount function may be the cause of the impulsive, poor self-regulatory actions associated with these health behaviours. These hypotheses are investigated extensively in Chapter 5 and, as such, we provide only this brief introduction in this chapter.

Self-control is defined as an individual's ability to refrain from undesirable behavioural tendencies (Lazzeretti et al., 2015) and, thus, literature exploring associations between self-control and weight loss is of high relevance. Two main strands of research exist regarding an association with weight loss; (1) general measures of self-control and (2) dietary specific measures of self-control including measures of eating restraint and dis-inhibited eating behaviour (Lazzeretti et al., 2015) i.e. an individual's ability to refrain from unhealthy dietary behaviours.

Three studies have been identified exploring general self-control. Two of these studies explore the effect of self-control on poor dietary habits, such as uncontrolled and emotional eating (Konttinen et al., 2009 and Kuijer et al., 2008). Both studies find a significant association between these variables i.e. individuals with low self-control are more likely to engage in poor dietary behaviours. The one study examining the relationship between general self-control and weight loss, however, finds no association between the variables (Munro et al., 2011). Although it should be noted that the sample size is small (n=54) and may lack the statistical power to detect an effect.

When examining dietary specific self-control and weight loss, past literature finds very little evidence of an association between these variables (Teixeira et al., 2005, Stubbs et al., 2011 and Lazzeretti et al., 2015). Two suggested explanation for this non-significant finding are presented by Teixeira et al. (2005); (1) Firstly, the heterogeneity of the assessment of dietary self-control, an issue discussed previously and (2) secondly, the suitability of pre-treatment measures of self-control. Developing self-control techniques and strategies often forms an important aspect of obesity treatment. Teixeira et al. (2005) argue that whilst individuals with high pre-treatment dietary self-control are likely to be successful, individuals with low pre-treatment dietary self-control may benefit more from interventions, thus, providing a hypothesis as to why no significant associations are observed.

Another hypothesis for the clustering of unhealthy behaviours is the effect of self-efficacy. Self-efficacy is defined as an individual's belief that they can accomplish the behaviour change necessary to achieve desired outcomes. For obesity, this may be the belief that one can successfully engage in healthy eating and physical activity behaviours to achieve the overall outcome of weight loss.

Self-efficacy forms a fundamental component of the Health Belief Model and, by extension, the COM-B model of behaviour change. It is, thus, believed to be an essential attribute to behaviour change. It can, therefore, be hypothesized that individuals with general low self-efficacy may struggle to exhibit healthy behaviours such as healthy eating, physical activity and healthy alcohol consumption. This hypothesis of the clustering of these health behaviours relies on the assumption that general self-efficacy can influence multiple situation-specific behaviours i.e. general low self-efficacy increases an individual's probability of behaviours such as smoking, physical inactivity and risky alcohol consumption. Supporting this assumption, Teixeira et al. (2005) find "*generalized measures of efficacy may be more predictive of outcomes*[28] *than scales that target perceived self-efficacy for specific behaviours, especially eating related*".[29] Considering general self-efficacy, there is a consistent finding amongst existing literature between high self-efficacy and successful weight loss (Lazzeretti et al., 2015).

A further fundamental component to the Health Belief Model and COM-B model of behaviour change, and a further theory for the clustering of poor health behaviours, is individual risk preference. Individuals who exhibit healthy behaviours are thought to do so partly because of the increased probability of better health in the future. Future health is, however, uncertain and not determined wholly by current behaviour. It is hypothesized that individuals who engage in unhealthy behaviours, such as smoking, physical inactivity and risky alcohol consumption, may, therefore, be less risk averse. This hypothesis is tested in Chapter 5 and, as such, we provide only this brief introduction in this chapter.

The following discussions will now turn to the health behaviour individually, discussing

[28] Studies examining general self-efficacy: Dennis and Goldburg (1996); Clifford, Tan and Gorsuch (1991); Pratt, McLaughlin and Gaylord (1992); Williams et al. (1996) and Teixeira et al. (2002).
[29] Studies examining dietary specific self-efficacy: Teixeira et al. (2002); Forster and Jeffery (1986); Yanovski et al. (1994); Fontaine and Cheskin (1997) and Traverso et al. (2000).

associations between these variables and weight loss.

2.6.18: Smoking

Contrary to the hypothesis of the clustering of unhealthy behaviours we find smoking is associated with higher percentage weight loss and a greater reduction in BMI at week ten. The coefficients are -0.40 (p-value= 0.01), -0.23 (p-value=0.02) respectively.

The relationship between smoking and obesity is complex. Nicotine suppresses appetite and speeds up metabolism (NHS, 2016). Further, on average, individuals who quit smoking will gain 5kg, due partly to the substitution of cigarettes for gratifying food (NHS, 2016). This has led to suggestions that it is the decline in smoking rates that has led to rise in obesity (Chou, Grossman and Saffer, 2004). Despite this suggested negative correlation, public health research consistently finds that, among sub-sets of the population, high obesity prevalence is associated with high smoking prevalence (Marmot et al., 2010).

2.6.19: Alcohol Consumption

Generally, a positive relationship exists between alcohol consumption and obesity status although it is thought to be non-linear (NOO, 2012). Further, research has found some evidence of a positive association between heavy drinking and weight gain (NOO, 2012).

The findings from this study shows that individuals who drink above recommended levels have worse weight loss outcomes. Specifically lower percentage weight loss (β=0.59 (p-value= 0.03).

In contrast, Fabricatore et al. (2009) find no association between number of alcoholic drinks per week and weight loss. The difference in findings between Fabricatore et al. (2009) and this study may be due to the different weight loss outcomes explored (see previous discussion), different measure of alcohol consumption (drinks vs. units) and the different time horizons at which successful weight loss was assessed (week 10 vs. week 52).

2.6.20: Diet

Past literature concerning dietary factors and weight loss tend to test the dietary aspects of interventions. Toubro and Astrup (1997), for example, conduct an RCT to assess the relative effectiveness of a VLED compared to a conventional diet. Although, in their review, Stubbs et al. (2011) conclude that it is the development of personalised habits and patterns of behaviours that may be more important to weight loss than adherence to strict recommendation. Studies regarding pre-treatment assessments of diet are less common although the diet specific measures of self-control (see earlier discussions) do provide some insights to pre-treatment eating behaviour.

On the contrary to what may be expected, individuals reporting a self-perceived more unhealthy diet achieve significantly better outcomes at week ten. Specifically a lower diet score is associated with higher percentage weight loss at week 10. The coefficients is 0.01 (p-value= 0.01).

One hypothesis for this finding is similar to a previous discussion regarding the relationship between initial BMI and weight loss. Individuals who, pre-treatment, report more unhealthy diets may gain most from the information and recommendations provided through the weight management service and subsequently experience better weight outcomes. If this hypothesis is true we may expect to see individuals reporting an unhealthy diet to exhibit higher initial BMIs. The relationship between perception of diet and initial BMI is, however, extremely weak (r=-0.08, p-value=<0.01).

This finding may also be related to the literature regarding previous dieting attempts. Previous dieting attempts, sometimes referred to as weight cycling, is the repeated process of losing and regaining weight. To elicit diet perception, we asked questions regarding both healthy eating habits and knowledge (See Appendix 10). It can be hypothesised that individuals who have more previous dieting experience are likely to score higher on the diet perception questions due to a general increased knowledge of what constitutes healthy behaviours. In their systematic reviews, Teixeria et al. (2005) and Stubbs et al. (2011) find "previous dieting attempts" or "weight cycling" as a robust predictor of poorer outcomes. This finding, thus, supports our finding of an association between an unhealthier perception of diet and better weight loss outcomes.

2.6.21: Physical Activity

General recommendations for modest weight loss (0.5-1kg per week) suggest individuals must reduce calorie intake or increase calorie expenditure by around 500kcal per day (US DHHS, 2010). For context, an average individual referred to the weight management service (aged 47, weight 96kg) would need to walk, at a moderate pace (3-4mph) for over an hour every day or run, at a moderate pace (7.5mph) for around 25 minutes to expend 500kcal (BHF, 2015). Given the physical limitations of obesity on ability to participate in exercise, many obese individuals find it difficult to lose weight through physical activity, thus, most weight management interventions tend to focus on dietary behaviours (Stubbs et al., 2011).

Whilst physical activity is not often used solely for weight loss, it has found to be an important factor in weight maintenance (Donnelly et al., 2009). Indeed we find a modest relationship between baseline energy expenditure and initial BMI ($r=0.61$, p-value=<0.01) suggesting physical activity may, to some extent, help control weight or reduce the rate of weight gain.

As a predictor of weight loss Teixeira et al. (2005) concludes that pre-treatment measures of physical activity are a poor predictor of weight loss. Our analyses agree with this conclusion finding a no significant relationships between exercise and weight loss outcomes.

2.6.22: Ethnicity

The final variable to be explored is ethnicity. The relationship between obesity and ethnicity is complex. The only representative data of UK obesity prevalence by ethnicity is the HSE (2004) which find the highest prevalence of obesity among Black African women and the lowest prevalence of obesity among Chinese individuals. Complexities exist due to debates around the definitions of obesity for non-white individuals with revised BMI thresholds being suggested for some ethic groups (NOO, 2011).

Due to only 30 individuals recorded as non-white, analysis of the non-white sub-categories of ethnicity is ill-advised. Using the binary variable “white” we find white individuals are significantly more likely to achieve higher percentage weight loss at week ten ($\beta=-1.45$, p-value=0.05), higher percentage weight loss at week twelve (β=-2.43, p-value=<0.01) and a greater reduction in their BMI at week twelve (β=-0.869, p-value=0.01). The marginal effects of ethnicity are large suggesting both a significant and important factor for weight loss. The low non-white sample (n=24) should, however, be noted. This finding reflects that of Fabricatore et al. (2009), the only other study identified exploring ethnicity, who also finds Caucasian ethnicity as a predictor of weight loss success.

2.7: Conclusion

Overall, initial weight loss and consistent attendance seem to provide the best predictors of successful weight loss with significant findings for all success measures and at both time points. For the week ten outcome it is also suggested that a relatively strong positive relationship between education and better weight loss outcomes exists. For week twelve outcomes it is further suggested that a relatively strong negative relationship between ethnicity and diabetes and weight loss outcomes exists.

The discussion present the result of analyses in the context of the current available literature and have focused on the main objective of the research which is how the evidence presented in this thesis supports the continuous improvement of weight management service. Reflecting back to discussion with Chapter 1 it is strongly acknowledged that the evidence presented here has much wider implications in the contexts of complex systems thinking, health inequalities and in the political environment. Whilst consistent attendance and initial weight loss have connotations for service delivery, the significant finding of a relationship between education and weight loss outcomes, in particular, has much broader implications. We have chosen not to present individual discussions regarding the broader implications of the research within disparate sections of individual chapters but rather to acknowledge their importance and, thus, dedicate a comprehensive and more appropriately extensive discussion within Chapter 6.

The chapter has presented the determinants of weight loss success for individuals engaged at the later stages of the programme. The following two chapters explored the broader programme, firstly, analysing factors associated with selection into two critical stages of the service and secondly, revisiting the weight loss outcomes but, this time, controlling for sample selection.

Chapter 3

Factors associated with attrition: Evidence from a publically funded weight management programme

3.1: Justification

The objective of research exploring predictors of attrition is to provide evidence to support the continuous development of effective weight management programmes. The identification of variables associated with attrition will enable policy makers to target certain individuals or groups of individuals who may drop out of treatment prior to achieving any significant benefits. As, previously stated, targeting may include activities such as extra support, tailored programmes and incentives (financial or otherwise) for participation. The requirement for and value of research exploring variables associated with attrition is reflected by Moroshko, Brennan and O'Brien (2011);

Individuals who terminate treatment early often leave before they have received the support they need to develop the skills and strategies required for weight loss and maintenance. Identification of factors contributing to weight loss intervention attrition will...facilitate offering special assistance, structure, therapist contact and/or a more targeted intervention for those at highest risk of dropout.

High attrition rates are associated with worse outcomes; worse treatment outcomes (Wadden, 1992) (Michell and Stuart, 1984); worse weight loss maintenance and; worse overall effectiveness (Davis and Addis, 1999). Reducing attrition in interventions may, thus, improve the overall effectiveness of weight-loss treatment and fully utilise current resources by maximising individual's exposure to weight management activities. Assuming the achievement of these short term benefits, we would also expect greater improvements to longer-term health (such as a reduced prevalence of diabetes) and the avoidance of costs associated with the management of poor health.

The quantity and quality of the literature exploring attrition marginally exceeds the literature examining weight loss (presented in the previous chapter). Sample sizes are slightly larger and sample characteristics are marginally less homogenous, however, whilst a decent number of studies exploring attrition exist (see Table 1.9), no reliable or consistent predictors of attrition have been found (Moroshko, Brennan and O'Brien, 2011).

Several limitations of the current evidence base have been identified. They are largely similar to the limitations of the weight loss research, presented in the previous chapter: the heterogeneity of evaluative methods; retrospective evaluative practices and; despite an improvement, sample selection and size remain an issue.

We significantly contribute to the current literature through the provision of research which does not suffer from the aforementioned limitations. The following dialogue does not repeat earlier discussions on the strengths of our research; however, it does outline factors of significance in respect to the literature on attrition.

The heterogeneity of the elicitation of variables is of concern in studies of attrition. Following on from discussions in the previous chapter, the inconsistent definition of attrition has resulted in difficulties in comparing past literature and in drawing robust conclusions suitable for practical advancements in treatment. From Table 1.9 we find attrition is measured via several methods;

- A binary variable indicating attendance at a fixed point in time (e.g. attendance to week 16 of a programme (Bennett and Jones, 1986))
- A binary variable indicating the length/frequency of attendance (e.g. attendance to ≥8 sessions (Bradshaw et al., 2010))
- A continuous variable measuring the length/frequency of attendance (e.g. number of sessions attended (Clarke et al., 1996))
- A binary variable indicating drop-out prior to meeting a weight loss target (Bautista-Castano et al., 2004).

Further, the timescale over which attrition is measured varies greatly. At the extremes, Ek et al. (1996) and Melin et al. (2006) assess attrition at 2 years after enrolment, whereas Seaton and Rose (1965) assess attrition as attendance to ≤1 session. The latter measure, whilst of interest, provides little value to an overall assessment of an intervention whilst, at the other extreme, studies measuring attrition over a longer time period tend to be a reflection of attrition from weight maintenance follow up studies rather than attrition from the initial weight loss programmes. Ek et al. (1996), for example, assess attrition at 2 years despite the weight loss treatment lasting as little at 3 weeks.

We previously outlined the definition of attrition applied in our analyses; engagement at week ten and week twelve of the service. Ten to twelve weeks from the start of a weight loss attempt is a critical point in time. If weight loss recommendations are followed this is the point in time when individuals should be experiencing levels of weight loss which will yield significant benefits to future health. The recommended rate of weight loss is between

0.5-1kg per week. The recommended overall weight loss is between 5-10% of initial body weight (NICE, 2010 and US DHHS, 2010). The average initial weight of individuals referred to the weight management service is 98kg, thus, between weeks ten and twelve is when individuals should be reaching these critical levels of weight loss. The duration of interventions commissioned globally for the treatment of obesity are often reflective of these recommendations (i.e. they last between 10 to 14 weeks, see Table 1.9). Our analyses are, thus, highly applicable to these programmes and explore a critical period in the management of excess weight. If programmes are to be successful they must seek to encourage engagement to these critical stages.

We have also previously discussed the non-retrospective nature of our analysis. This is of particular importance when considering attrition. During the service development process, particular attention was given to the structure of data collection. Due to expected levels of attrition, great effort was made to collect the data of interest early in the weight management programme to ensure complete records and subsequent statistical analyses. Moroshko, Brennan and O'Brien (2011) highlight that a significant issue of past research has been the reliance on readily available data which was collected for the purposes of monitoring weight outcomes but lacks a theoretical reasoning for collection when examining behaviour, or post-intervention data collection which often suffers from reduced samples and sample selection issues due to non-response to these follow up surveys.

As a result of our planning, we contribute to the current literature through the analysis of a rich and robust dataset containing numerous variables of both academic and practical interest.

A handful of larger scale studies exist exploring attrition from weight management programmes. Three studies assess the outcomes of ≥1,000 individuals, however, the wider applicability these studies is limited due to various characteristics of the research. Bautista-Castano et al. (2004) (n=1,018) assess a binary outcome which indicates that an individual has dropped-out before they have met a pre-defined weight loss target. For the assessment of long term health benefits this outcome is of great interest, however, the large variations in treatment duration (mean: 4.71 months, standard deviation: 3.71 months) result in a limited generalisability of the findings. As previously mentioned, Seaton and Rose (1965) (n=1,000) define attrition as attendance to ≤1 session which has limited value to strategies to encourage individuals to engage to critical stages of weight loss (described previously). Finally, Grave et al. (2005) exhibit the opposite issue as they assess engagement at 12 months. Even with a higher average initial BMI (38.2), which may require an extended period of time for individuals to meet recommend levels of weight loss, 12 month assessments are more reflective of attrition from weight maintenance attempts than weight loss attempts.

We significantly contribute to the current literature through the utilisation of the records of 2,892 individuals and provide predictors of attrition from the 2,087 individuals who commence the weight manage service.

3.2: Introduction

Evidence suggests that rates of attrition range between 10% and 80% (Moroshko, Brennan and O'Brien, 2011). Moroshko, Brennan and O'Brien (2011) published a systematic review of literature identifying factors associated with attrition in weight loss interventions resulting in the summarisation of sixty-one studies (see Table 1.9). The review was limited to interventions for the treatment of overweight and obese (BMI>30) adults (aged between 18 and 65 years), a focus suitably aligned with the scope of the programme analysed in this thesis. When evaluating past literature studies from this review of lifestyle interventions post-weight loss surgery were generally disregarded, as it was felt the individuals assessed in these studies differed considerably from the population of interest. A literature search was performed to identify research not included in Moroshko, Brennan and O'Brien's (2011) review and consisted largely of research published post 2011. Excluded from this search were studies of attrition from bariatric surgery, paediatric interventions, post-partum interventions and research involving post-treatment, self-reported reasons for drop-out. This is reflective of the literature search performed for studies of predictors of weight loss in the previous chapter. This activity resulted in the identification of fifteen additional studies (see Table 1.9).

An overview of the findings of previous research exploring predictors of attrition from weight management programmes is presented in Table 3.1. An overview of the literature reveals much inconsistency with many variables presenting mixed or merely suggestive relationships. It is also worth highlighting that whilst it may seem that much past research has studied personality factors the results presented in the table are drawn from only seven studies.

Variable	Relationship
Socio-Demographic	
Ethnicity (non-white)	Positive
Marital Status	Suggestive (+)
Age	Suggestive (-)
Education	Suggestive (-)
Male	None
Socio Economic Status	None
Occupational status	None
Weight factors	
Weight/Shape concerns	Positive
Weight cycling	Positive
Early weight loss	Negative
Initial body weight or BMI	Mixed
Hip and waist circumference	Mixed
Aspects of the service	
Realistic weight loss goals and expectations	Positive
Health behaviours	
Binge eating	Positive
Dieting self-efficacy / Weight loss self-efficacy	Negative
Physical activity	Suggestive (+)
Smoking	Suggestive (+)
Emotional eating	Suggestive (+)
Food consumption patterns	Mixed
Alcohol consumption	None
Eating behaviour disorders	None
Self-control in eating	None
Perceived hunger	None
Physical Health	
Diabetes	Suggestive (+)
Osteoarthritis	Suggestive (+)
Absence of fibromyalgia	Suggestive (+)
Prescribed medication	Mixed
Obesity related disease / Medical History	Mixed
CVD	None
High Blood Pressure	None

Mental health	
Psychological and obesity related psychological disturbance	Positive
Depression	Positive
Anxiety	Suggestive (+)
Self Esteem	Suggestive (-)
Stress	Mixed
Presence of psychiatric disease Psychological function	None
Life satisfaction and validity	None
Pyscho-pathological distress	None
Personality	
Impulsiveness / Lack of inhibition	Suggestive (+)
Passiveness	Suggestive (+)
Lower harm avoidance	Suggestive (+)
Lower energy level	Suggestive (+)
Lower organisation	Suggestive (+)
Lower responsibility	Suggestive (+)
Narrow breathe of interest	Suggestive (+)
Dominancy	Suggestive (+)
Ego strengths	Suggestive (+)
Social Adjustment	Suggestive (+)
Narcissism	Suggestive (+)
Autonomy need support and satisfaction	None
Social adjustment and defence mechanisms	None
Difficulty on relying on others support	None
General personality	None
Undefined	
Travel distance	Positive
Social support	Negative
Weight loss self-efficacy	Negative
Work or home problems	Suggestive (+)
Lack of time	Suggestive (+)
Weight loss motivation	Suggestive (-)
Financial issues	Mixed
Treatment mode	Mixed

Table 3.1: Factors associated with attrition: A summary of the existing evidence[30]

[30] Adapted from Moroshko, Brennan and O'Brien (2011) and subsequent literature search results.

As well as contributing evidence to existing hypotheses, new hypotheses are presented. Unexplored variables include the effect of children, consistency of attendance, perception of local area, referral type, time to treatment and some new measures of personality on attrition. These hypotheses and the theoretical foundations are presented in later discussions (see Section 3.4).

The previous chapter explored determinants of weight outcomes at weeks 10 and 12 of the service. This chapter adds a second dimension to the evaluation through the exploration of determinants of selection into these stages of the service.

The exploration of attrition utilises the data collected from the weight management programme outlined in the previous chapter. The variables explored are the demographics, weight factors, aspects of the programme, health behaviours, physical health factors, mental health factors and personality traits described previously.

3.3: Results

The following tables present the results of the maximum likelihood estimations exploring the associations between variables outlined in Table 2.5 with attrition. For clarity, Table 3.2 outlined the details of each of two results tables presented in this chapter. The first table presents the results for engagement at week ten with the second table reporting the results for engagement at week twelve.

The dependent variables ('engagement at week 10' and 'engagement at week 12') are binary variables and, thus, are estimated using probit models. As previously outlined, the probit model is a regression where the dependent variable is binary. It employs a probit link function and is estimated using the maximum likelihood procedure. The probit function takes any argument between $\pm\infty$ and transforms it into a number between 0 and 1. The probit link function is:

$$\text{prob}(Y=1 \mid \mathbf{X}) = \Phi(\mathbf{X}'\beta) \tag{1}$$

where $\mathbf{X}$ is a vector of individual characteristics and control variables, β is a vector of estimated coefficients and Φ is the cumulative standard normal distribution. One can link a latent index $y^* = \mathbf{X}'\beta + \varepsilon$ to the indicator variable y, which is equal to -1 or 1: $y = 1$ when $y^* > 0$, and otherwise y is equal to -1. The conditional log-likelihood is then

$$\ln L(\beta ; y, \mathbf{X}) = \textstyle\sum_i \left[(\ln \Phi(\mathbf{X}'\beta) \times \mathbf{I}(y_i = 1)) + (\ln (1- \Phi(\mathbf{X}'\beta)) \times \mathbf{I}(y_i = -1)) \right] \tag{2}$$

where **I**(·) is the indicator function, and y_i =1(−1) denotes the choice. The latent index y* is defined as a linear function of the characteristics in vector **X**.

Table No.	Dependent Variable	Explanatory Variables	Sample	Estimation Method
3.3	Engagement at week 10	32 variables outlined in Table 2.5	All individual starting the service	Maximum Likelihood
3.4	Engagement at week 12	32 variables outlined in Table 2.5	All individual starting the service	Maximum Likelihood

Table 3.2: Summary of the Results Tables in Chapter 3

Table 3.3: Engagement at week 10
Maximum Likelihood Estimation (n=1,468)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	-0.71	0.65	0.27	-1.98	0.56
Demographics					
Male	0.11	0.16	0.51	-0.21	0.42
Age	0.02	0.02	0.26	-0.01	0.05
Age squared	0.00	0.00	0.59	0.00	0.00
White (ethnicity)	0.01	0.33	0.97	-0.64	0.66
Indices of deprivation	-0.02	0.02	0.28	-0.05	0.01
Partner	0.08	0.08	0.33	-0.08	0.24
Presence of children	-0.34	0.11	0.00	-0.56	-0.12
Employed	0.02	0.09	0.82	-0.15	0.19
Degree level education	0.05	0.10	0.61	-0.15	0.25
Perception of local area	0.00	0.00	0.32	0.00	0.01
Weight factors					
BMI (initial)	0.01	0.01	0.13	0.00	0.03
Weight change (kg) week 2	-0.11	0.02	0.00	-0.14	-0.07
Aspect of the programme					
Self-referred	-0.03	0.08	0.67	-0.18	0.12
Days (referral to registration)	0.00	0.00	0.36	0.00	0.01
Days (registration to start)	-0.01	0.00	0.01	-0.02	0.00
Consistent attendance	0.05	0.07	0.49	-0.10	0.20
Health behaviours					
Smokes	-0.28	0.12	0.02	-0.51	-0.04
Excess alcohol consumption	0.14	0.14	0.31	-0.13	0.41
Perception of diet	0.00	0.00	0.06	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.35	0.00	0.00
Physical health					
Disabled	0.35	0.20	0.08	-0.04	0.74
Cardiovascular disease	0.10	0.16	0.56	-0.22	0.42
Mobility problems	0.12	0.10	0.22	-0.07	0.31
Diabetes	0.21	0.14	0.14	-0.07	0.49
Hypertension	-0.07	0.11	0.49	-0.28	0.13
Mental health					
Depression	-0.24	0.12	0.05	-0.49	0.00
Stress	-0.05	0.15	0.75	-0.35	0.25
Personality					
Openness	0.00	0.00	0.84	0.00	0.00
Neuroticism	0.00	0.00	0.97	0.00	0.00
Conscientiousness	0.00	0.00	0.84	0.00	0.00
Agreeableness	0.00	0.00	0.93	0.00	0.00
Extroversion	0.00	0.00	0.51	0.00	0.00

Table 3.4: Engagement at week 12
Maximum Likelihood Estimation (n=1,468)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	-0.95	0.61	0.12	-2.13	0.24
Demographics					
Male	0.17	0.14	0.24	-0.11	0.44
Age	0.01	0.02	0.49	-0.02	0.04
Age squared	0.00	0.00	0.96	0.00	0.00
White (ethnicity)	0.07	0.31	0.83	-0.54	0.68
Indices of deprivation	-0.01	0.01	0.50	-0.04	0.02
Partner	-0.03	0.08	0.70	-0.18	0.12
Presence of children	-0.25	0.10	0.01	-0.45	-0.05
Employed	0.01	0.08	0.86	-0.15	0.17
Degree level education	0.02	0.09	0.85	-0.16	0.20
Perception of local area	0.00	0.00	0.71	-0.01	0.00
Weight factors					
BMI (initial)	0.03	0.01	0.01	0.01	0.04
Weight change (kg) week 2	-0.09	0.02	0.00	-0.12	-0.06
Aspect of the programme					
Self-referred	0.06	0.07	0.40	-0.08	0.20
Days (referral to registration)	0.00	0.00	0.70	0.00	0.01
Days (registration to start)	-0.01	0.00	0.01	-0.02	0.00
Consistent attendance	0.32	0.07	0.00	0.19	0.46
Health behaviours					
Smokes	-0.21	0.12	0.08	-0.43	0.02
Excess alcohol consumption	-0.05	0.12	0.66	-0.30	0.19
Perception of diet	0.00	0.00	0.37	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.09	0.00	0.00
Physical health					
Disabled	0.09	0.17	0.58	-0.24	0.43
Cardiovascular disease	0.21	0.15	0.16	-0.08	0.49
Mobility problems	0.07	0.09	0.44	-0.10	0.24
Diabetes	0.25	0.13	0.04	0.01	0.50
Hypertension	-0.11	0.10	0.23	-0.30	0.07
Mental health					
Depression	-0.17	0.12	0.16	-0.40	0.06
Stress	-0.07	0.14	0.62	-0.35	0.21
Personality					
Openness	0.00	0.00	0.11	-0.01	0.00
Neuroticism	0.00	0.00	0.65	0.00	0.00
Conscientiousness	0.00	0.00	0.82	0.00	0.00
Agreeableness	0.00	0.00	0.83	0.00	0.00
Extroversion	0.00	0.00	0.95	0.00	0.00

3.4: Discussion

This section discusses the results of the analysis. The results will be discussed in the context of previous literature summarised previously in Table 1.9.

As previously stated, the literature summary table from Moroshko, Brennan and O'Brien (2011) has been adapted and expanded to include further relevant research, specifically research published post-2011. This literature search was limited to non-surgical, non-pharmacological weight loss programmes. Programmes aimed at children and post-partum women were also excluded. This summary of the literature has been presented previously in Table 1.9 in Chapter 1.

Attrition serves as a secondary measure of success in evaluations of weight management services and as such, many of the theoretical justifications and hypothesised associations between the variables and attrition are similar to those presented in Chapter 2 of the associations between the predictor variables and weight loss. The following discussions will not, however, compare and contrast the findings of these two measures of success (weight loss and attrition). In the following chapter, analyses are brought together in an examination of weight loss outcomes controlling for attrition, and as such, comparative discussions of the results are more appropriate and of more relevance in the context of the following chapter.

3.4.1: Partner

The hypothesised relationship between having a partner and attrition is based on previous discussions regarding the positive influence of social support. In their systematic review, Moroshko, Brennan and O'Brien (2011) identify three studies of the effect of social support. All three studies find increased social support lowers the probability of drop out from weight management. The literature is divided between two distinctive theoretical strands of social support. Yass-Reed, Barry and Dacey (1993) elicit measures of "structural" support i.e. the availability of significant others such as partners, family members, friends etc., by asking participants to quantify close friends. They also ask participants to quantify people who "*annoy the individual about his or her weight*", a differing approach but, arguable, also social support. Fowler et al. (1985) and Huisman et al. (2010), however, elicit measures of "functional" support i.e. an individual's perception of available support, by asking participants to rate their expected support from family members (Fowler et al., 1985) and from others generally (Huisman et al., 2010). Considering the distinction between the types of social support, our study is, loosely, a measure of structural support, as we record the presence of a partner rather than expected or perceived support from them.

Research utilising theories of social support in the design of interventions to increase successful outcomes within weight management are of particular interest to this discussion. Much research into the effect of group vs. individual interventions is available with a general consensus that group interventions are more effective (Heshka et al., 2003 and Williams et al., 1996). Two, more original, areas of research are (1) financial deposit and group based rewards for weight loss and (2) spouse based weight loss commitment contracts (Verheijdenet al., 2005).

Jeffery et al. (1983) conducted a trial to assess the effectiveness of financial deposits and group based rewards. In their research they assessed the weight outcomes of eighty-three men over a 15-week weight loss programme. All participants entered into a contract in which they deposited money which was returned upon successful weight outcomes. Participants were randomly assigned to an individual contract or a group contract whereby deposits where returned on mean group performance. There was no control group that consisted of no financial incentives. The group contracts resulted in significantly greater weight loss and maintenance compared to the individual contracts. Mean weight loss at three months, for example, was 30.9lbs for the group contracts compared to 26.6lbs for the individual contracts.

Murphey et al. (1982) conducted a trial to assess the effect of spouse involvement on weight loss. The study was a 2 x 2 factorial design. Ninety-seven couples were randomly assigned to either attend weight management sessions alone or with a spouse and also signed contingency contracts either individually or jointly (spouses). The authors conclude that partner involvement in weight management yields the most successful outcomes finding individuals attending weight management sessions with their partners lost significantly more weight than those who attended individually.

Interestingly, despite the theoretical and empirical findings for the positive impact of social support for behaviour change, the past literature regarding marital status and attrition is far from conclusive. Several previous studies have found no significant association between these variables[31] which is reflected in our findings. From our analyses the estimated coefficient is engagement at week 10 of the service is 0.08 (p-value=0.33) and in the week 12, -0.03 (p-value=0.70). Of the few studies that do find a significant relationship all observe a positive relationship i.e. married individuals are more likely to drop out of weight management interventions than non-married individuals.

3.4.2: Education

Social support may also be an influential factor on the relationship between education and attrition. More educated individuals tend to exhibit larger social networks, for example, they are more likely to be married and have more friends (Berkman, 1995). It is hypothesised that these social networks provide the required social support for successful outcomes whether this be emotional and motivational support or more tangible factors such as financial support or childcare (Cutler and Lleras-Muney, 2006).

There is strong evidence of an association between education and static weight status, i.e. as education attainment increases the prevalence of obesity decreases (Craig and Mindell, 2012 and NOO, 2014). If we assume educated individuals socialise with others with similar characteristics (i.e. similar levels of education) the hypothesis of education as a predictor of successful outcomes may also be underpinned by the theoretical model of social norms. Social norms theory suggests that individual's behaviour is influenced by their perception of how their peers think and behave (*Perkins and Berkowitz, 1986*)[32]. If peers are more likely to be of a healthy weight, this may influence eating and physical activity behaviours of

[31] Michelini et al., 2014, Bennett and Jones (1986), Inelmen et al. (2005), Huisman et al. (2010), Grossi et al. (2006), Pekarik et al. (1984), Mitchell and Stuart (1984), Fabricatore et al. (2009) and Bradshaw et al. (2010).

[32] Social opportunity also forms a critical component of the COM-B model of behaviour change.

individuals to conform to this social norm. In the context of the weight management programme, social norms may encourage more educated individuals to attend for a longer duration to maximise the probability of achieving a weight status reflective of peers.

In the previous chapter the hypothesis between education and weight loss was supported by the notion of the benefits of increased cognitive skills. Certainly, in other areas of healthcare, an association between compliance to more complex treatments and higher education have been observed. Goldman and Smith (2002), for example, find an association between education and compliance to treatment for AIDS and diabetes; two conditions requiring demanding and relatively complex management (Cutler and Lleras-Muney, 2006). Whilst attendance to weight management sessions is not considered complex, attendance is a reflection of overall engagement with the behaviour change recommendations which, as previously discussed, is likely to be influenced by cognitive ability.

Despite these discussions, the theoretical association between education and attrition is less clear than for education and weight loss. Of past studies that find a significant association[33], all conclude that higher education is associated with compliance as expected from our hypotheses. The majority of research, however, finds no significant association between the variables. Our research reflects this finding as we observe no significant association between education and attrition. The estimated coefficient for engagement at week 10 of the service is 0.05 (p-value=0.61) and in the week 12, 0.02 (p-value=0.85). Despite our insignificant findings when exploring attrition within the service, when utilising logistic regression to explore factors associated with starting the service (see Appendix 15)

[33] Grossi et al. (2006), Chang, Brown and Nitzke (2009), Fabricatore et al. (2009), Bradshaw et al. (2010) and Elfhag and Rössner (2010).

we find that individuals educated to a degree level or higher are more likely to start the service (i.e. attend at least week 1) (β=0.28, p-value=0.04); 92.6% of individuals with a degree level qualification or higher start the service compared to 87.7% of individuals who do not.

3.4.3: Presence of children

In the previous chapter it was hypothesised that having children may provide increased social support and/or increased external motivation for successful outcomes with increased external motivation based theoretically on the Health Belief Model.

Hypotheses of a reversed association; having children is associated with increased probability of attrition; arise from the effect of physical constraints such as lack of time. The physical capability to change behaviour is reflected in the COM-B model of behaviour change as a critical component. Research exploring attrition from paediatric weight management programmes find the most consistently reported reasons for attrition are "scheduling issues" and "programme not meeting family needs or expectations" (Skelton and Beech, 2011). A lack of time and the ability to fuse new behaviours and habits into a family environment are two reasons that have been previously suggested to explain the association between having children and poor outcomes in adult weight management programmes.

We find having children is associated with a lower probability of engagement to both week ten (β=-0.34, p-value=<0.01) and twelve (β=-0.25, p-value=0.01) of the service. Whilst the difference between the two groups (i.e. those with and without children) is small, they are significant. Seventy-five percent of individuals without children are engaged at week ten compared to 71% of individuals with children. The same difference exists at week twelve where 59% of individuals without children attend compared to 55% of individual with children.

3.4.4: Physical Health

The presence of obesity related health conditions was previously suggested as a further factor which may increase motivation for success. Several studies exploring the presence of obesity related co-morbidities exist. Although a post-surgical study, when assessed as a group of conditions, Pontiroli et al. (2007) finds no significant association between the presence of obesity related diseases and attrition. Assessing the effect of all conditions as a single variable does not fully reveal the relationship between individual co-morbidities and attrition. A review of past research suggests studies examining the effects of individual or more appropriately grouped conditions (such as grouped cardiovascular diseases) on attrition may be more promising. Past research has considered the following conditions; type-2 diabetes, osteoarthritis, CVD, heart disease and high blood pressure.

Moroshko, Brennan and O'Brien (2011) identify five studies exploring the presence of type-2 diabetes and attrition. Three find no significant association whilst the remaining two find patients without diabetes are more likely to drop out. Our results are consistent with the later finding. We find individuals with diabetes are more likely to be engaged in the final week of the service ($\beta=-0.25$, p-value=0.04). Sixty-one percent of individuals with diabetes were engaged at the final week of the service compared to 54% of non-diabetics. Regarding other physical health conditions, however, we find no significant association between the presence of obesity-related co-morbidities and attrition.

One possible explanation for the significant finding for diabetes but not other conditions may be the increased perceived association between diabetes and obesity. Our hypothesis is founded on the theory that the presence of a health condition increases the perceived severity of obesity and potential benefits of weight loss. For this assumption to hold, individuals must be aware and accept the relationship between obesity and the condition. If individuals perceive a strong association between diabetes and obesity, and/or a strong association between effective management of diabetes and the recommended behaviour changes, this may explain the findings within our analyses.

Whilst conditions were appropriately grouped, an extension to the research may be an analysis of individual conditions. In particular, summary statistics and a two sample t-test exploring the effect of osteoarthritis warrants further investigation. Sixty-seven percent of individuals with osteoarthritis attend week twelve compared to 54% of individuals without the condition. This finding is in stark contrast the findings of Busetto et al. (2009) who find having osteoarthritis increases the probability of attrition.

3.4.5: Age

Looking to past research, the relationship between osteoarthritis and attrition may partly be explained by the association between age and attrition; due to the conditions increasing prevalence with age. Moroshko, Brennan and O'Brien (2011) conclude that "*older age may serve as a protective factor against attrition*" and among studies that find age to be a predictive factor of attrition, overwhelming, report a negative relationship between the variables. Indeed, two theoretically formed hypotheses were presented in the previous chapter for this association between age and successful outcomes. In summary older individuals may exhibit more successful outcomes due to; increased lifestyle stability allowing for the successful formation and maintenance of new behaviours and/or an increased efficiency in developing coping and behaviour management strategies which support weight loss efforts.

We, however, find no evidence of an association between age and attrition. Despite the conclusions of Moroshko, Brennan and O'Brien (2011), the majority of studies that examine age find no significant association between the variables, thus, the findings of our analysis are not unexpected.

3.4.6: Employment

The stability of employment for habit formation was the hypothesis for a positive relationship between employment and weight loss. Wanrooy et al. (2011) suggests that, in the UK, there has been an increase in non-standard working hours, such as shift working and zero-hour contracts. Whilst definitions vary, Eichhorst and Marx (2015) estimate around 25% of the UK workforce to be employed in non-standard work. Employment may, therefore, result in logistical factors such as lack of time or an inability to attend a regular session and an inevitable friction cost to individuals resulting from having to research and attend alternative groups. Despite this hypothesis the past literature finds no significant association between employment status and attrition and we reflect this finding in our own study. The weight management programme was designed to be flexible to individual's needs with multiple sessions available to attend and an administrative hub to support the search for alternative provision if individuals found employment or other factors to be a barrier to engagement.

3.4.7: Local Area

Previous discussion regarding the theory of social norms is one strand of research assessing the influence of the external environment on outcomes. We assess individual's perception of a broad range of external factors which may influence attrition. We hypothesise that the unhealthier an individual perceives their local area, the higher the probability of attrition. This hypothesis is based on the influence of the practical and logistical constraints; i.e. one's reduced physical capability of behaviour change resulting from residing in an area which can be seen to discourage healthy behaviour. Attendance to weight management sessions is likely to be influenced by an individual's ability to engage successfully with behaviour change recommendations. If the immediate environment is unsupportive of these changes (there is, for example, a lack of local shops selling healthy food), individuals may perceive the programme to be unsuitable or too difficult. They may subsequently struggle to adhere to the programme's recommendations which may ultimately result in drop-out. This hypothesis is supported by previous discussions regarding the effect of the complexity of treatment on compliance (Section 3.4.2: Education). Individuals who reside in increasingly obesogenic environments are likely to be required to make increasingly substantial lifestyle changes to achieve objectives. To adhere to the dietary recommendations, for example, they may have to find new places to shop and travel further to acquire certain food. These additional behaviours introduce additional friction costs to behaviour change and may result in discontinuation of treatment.

We, however, find no evidence of an association between perception of local area and attrition at either week 10 or 12. When exploring variables association with starting the service, however, we find that individuals who perceive their local area to be healthier are more likely to start the service. This finding is in line with the hypothesis presented it is worth noting that the estimated effect size is minimal (β=0.01, p-value=0.02). To contextualise, perception of local area was elicited through a series of questions resulting in a score out of 100. The average score was 63.5. Of individuals' scoring above average (i.e. perceive their local area to be more healthy), 89.6% started the service. The uptake rate among individuals scoring below the average (i.e. perceive their local area to be less healthy) was 87.6%, representing a 2 percentage point difference between the two groups. Past research in this area has tended to focus on logistical factors such as travel time to treatment (Bautista-Castano et al., 2004) or financial restraints (Mavis and Stoffelmayr., 1994) to explain attrition. No studies to date have assessed individual's perception of their local area on attrition; therefore, there is no empirical evidence by which to compare our results.

3.4.8: Personality

Whilst several aspects of personality have been considered in the past literature, the amalgamated findings presented in Table 3.1 are drawn from only a handful of studies. A limitation of the past research, that is particularly applicable to studies of personality and attrition, is the heterogeneity of methodology used to assess personality[34]. Personality is a multifaceted construct and, thus, it is not surprising that assessments of personality traits are so varied. We utilise the BFI methodology as it provides a validated method for the assessment of personality (McCrae and Costa, 1987 and Muck, Hell and Gosling, 2007). Further, this method has been previously utilised within assessments of weight management interventions and subsequent analyses have indicated promising results.

The five aspects of personality examined are; openness, conscientiousness, extroversion, agreeableness and neuroticism. Jerant et al. (2009) examined the predictive nature of the BFI of personality on missing data in an RCT concerned with supporting individuals to manage a variety of chronic diseases. Whilst many aspects of Jerant et al.'s (2009) study differ quite substantially from our analyses, the underlying principle of an association between personality (measured using the BFI) and attrition is of high relevance. We consequently present the same hypothesised associations;

Firstly, we expected the probability of attrition to be greater for individuals scoring more highly in "Neuroticism". Individual with neurotic tendencies may lack the emotional stability and impulse control required for continued participation. Neuroticism is also associated with depression which past studies have found to be predictive of attrition (see Table 3.1). For all other personality traits we expect to observed lower probabilities of attrition. Individuals scoring more highly in "Openness" tend to exhibit a preference for new experiences and a tendency to be relatively independent, thus, more likely to attend the

[34] Personality tests include: **Karolinska Scales of Personality** (KSP) (Hjordis and Gunnar, 1989), Minnesota Multiphasic Personality Inventory (Keegan, Dewey and Lucas, 1987), Temperament and Character Inventory (De Panfilis et al., 2008), Jackson Personality Inventory (Pekarik et al., 1984) and Eysenck Personality Questionnaire (Bennett and Jones, 1986).

treatment sessions. For individuals scoring more highly in "Conscientiousness" lower rates of attrition were expected due to a tendency for these individuals to be organised and have an aptitude for self-discipline. Individuals scoring more highly in "Agreeableness" have a tendency to be co-operative, thus, are likely to increase adherence to treatment. Finally, extroverts tend to exhibit positive emotions and are highly sociable, thus, it is expected that these individuals will benefit from the group setting and are less likely to drop-out.

In line with the hypotheses, Jerent et al. (2009) found that higher levels of agreeableness and conscientiousness significantly reduced the probability of attrition. We, however find no significant association between any of the five traits with attrition from weight management. The coefficients for all personality traits in the week 10 and 12 analyses are 0.00 and in all cases are statistically insignificant.

Interestingly, when exploring factors associated with starting the service, however, we find those scoring more highly on the measure of agreeableness are less likely to start the service (β=-0.01, p-value=0.01). Whilst, this finding is in contract to those by Jarent et al. (2009) it is worth noting the relatively small estimated effect size. The agreeableness construct was elicited through a multiple questions resulting in a score out of 100 (see Appendix 10). The average score was 73.7. Of individual's scoring above average (i.e. those more agreeable), 87.5% started the service. The uptake rate of individuals scoring below the average (i.e. those less agreeable) was found to be only 2.1 percentage points higher at 89.7%. Due to this relatively small estimated effect size this finding is more of academic interest, due to its conflict with both theoretical and previous empirical conclusions, than from a practical, interventional perspective.

3.4.9: Health Behaviours

An aspect of personality previously discussed as an explanation for the clustering of unhealthy behaviours is self-efficacy (i.e. an individual's level of confidence regarding their ability to engage in behaviours necessary for successful outcomes). Similarly, it is hypothesised that low self-efficacy may also be associated with the clustering of non-compliance to healthy behaviours i.e. an individual with low self-efficacy will be more susceptible to attrition from multiple healthy behaviours such as weight loss, physical activity, smoking cessation and alcohol treatments.

Certainly, within weight management, findings from previous studies, suggest higher self-efficacy is a relatively strong predictor of reduced attrition. Eight studies have been identified examining the relationship between self-efficacy and attrition from weight management interventions. Whilst three find no relationship[35]; five find a significant association[36,37]. Further, both general and situation-specific self-efficacy predicts attrition. Of the five studies finding a significant association, Ahnis et al. (2012) assess general self-efficacy, whilst the other four studies assess dieting and weight loss self-efficacy.

In a review of the effect of self-efficacy on health, Stretcher et al. (1986) found low general self-efficacy to also be a consistent predictor of the discontinuation of alcohol treatment,

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[35] Huisman et al. (2010), Fowler et al. (1985) and Prochaska et al. (1992).

[36] Marcus, Wing and Hopkins (1988), Fontaine and Cheskin (1997), Edmunds, Ntoumanis and Duda (2007), Bernier and Avard (1986) and Ahnis et al. (2012).

[37] Self-efficacy is measured through questionnaires. For example, Fontaine and Cheskin (1997) utilise the Weight Efficacy Lifestyle Questionnaire (WEL; Clark et al., 1991); a 20-item self-report questionnaire that assesses five dimensions of efficacy for weight management. The items are answered on a 10-point scale (0 to 9) with higher scores indicating greater confidence in resisting the desire to eat in various situations and circumstances.

non-compliance to exercise programmes and relapse in smoking cessation studies. This finding provides evidence for our assumption that general self-efficacy can influence multiple situation-specific behaviours, thus, supporting the hypothesis for its role in the clustering of attrition from healthy behaviours.

It was also previously discussed that impulsiveness and lack of self-control may also contribute to the clustering of unhealthy behaviours**.** Similarly, it is hypothesised that these factors may also be associated with the clustering of non-compliance to healthy behaviours i.e. an individual with high impulsiveness and low self-control will be more susceptible to attrition from multiple healthy behaviours such as weight loss, physical activity, smoking cessation and alcohol treatments.

It was suggested that individual's exhibiting a hyperbolic discount function may make behaviour change plans in one period but subsequently deviate from them at a later stage. This may materialise as commencing, but later defaulting, from treatment. General impulsiveness and general lack of self-control may explain the clustering of attrition from healthy behaviours if we accept the assumption that these characteristics can influence multiple situation-specific behaviours, i.e. general impulsivity or general lack of self-control increases an individual's probability of attrition from obesity treatment, non-compliance with physical activity opportunities and relapse from both smoking and alcohol treatments.

Whilst we do not measure attrition from other health behaviours we do assess the relationship between attrition from the weight management service and engagement in other unhealthy behaviours (poor diet, lack of exercise, smoking and risky alcohol consumption). We aim to broaden current discussions on the clustering of static measures of unhealthy behaviours to consider their relationship with the probability of behaviour change i.e. the association between health status and probability of successful engagement in behaviour change.

The following discussions will now turn to the health behaviours individually, discussing associations between these variables and attrition.

3.4.10: Diet

One study is identified with a comparable assessment of healthy eating. Huisman et al. (2010) examine the variable "healthy eating", comprising of an assessment of the consumption of fat, fruit, vegetables, salt, red meat, sweets and snacks. We reflect the findings of Huisman et al. (2010) observing no significant association between perception of diet and attrition.

A more consistent predictor of attrition from weight loss interventions is number of past dieting attempts or "weight cycling". Weight cycling may be viewed as a cyclical pattern of the time inconsistent behaviour described previously. The nature of weight cycling, as a repeated pattern of weight gain and weight loss, suggests that impulsivity and self-control characteristics may persist over time. In support of this, Elhag and Rössner (2005) find that cognitive restraint (i.e. a conscious determination to refrain from eating to control body weight) acts a mediating factor[38] for weight maintenance; an indication of the effect of self-control on engagement in healthy behaviours over time.

3.4.11: Smoking

Preferences resulting in impulsive behaviour, uncontrolled by self-discipline form the theoretical basis for the relationship between smoking and attrition. It is suggested that both behaviours signify evidence of an impulsive tendency and decreased self-control. We, therefore, hypothesise that individuals who smoke are more likely to drop out of the weight management service. Indeed, of the five studies identified by Moroshko, Brennan and O'Brien (2011), three find this positive association between smoking and attrition[39]. We also find smokers are less likely to be engaged at week ten of the service. The coefficient is -0.28 (p-value=0.02). Seventy-three percent of non-smoking individuals are engaged at weeks 10, compared to 60% of smokers. The effect of smoking on attrition is compounded by findings from the logistic regression exploring factors associated with registering for the service. In this analysis we find further evidences that smokers are less likely to engage, in this case register for the service, than non-smokers (β=-0.29, p-value=<0.01). Whilst, 83.2% of non-smokers register for the service, only 74.5% of smokers do so. This in part may explain previous finding of a positive association between smoking and successful weight loss. In Chapter 2 individuals who were not engaged at week 10 and 12 were excluded from analyses. Due to significant drop-out both prior to starting and during the service we may, in fact, have limited our analyses to only the most motivated smokers, thus, observed more successful outcomes for this group.

[38] **"***Mediators are the mechanisms that can identify why a treatment effect is achieved"* Elfhag and Rössner (2005).
[39] Clark et al. (1996), Greenburg et al. (2009) and Bradshaw et al. (2010).

3.4.12: Physical Activity

The association between physical activity and attrition is based on the same theoretical constructs of self-efficacy, impulsivity and self-control. It is suggested that engagement in physical activity signifies increased self-efficacy and self-discipline resulting in a negative correlation with attrition. Previous studies finding a significant relationship include Teixeira et al. (2004), Clark et al. (1996) and Busetto et al. (2009). As predicted, all three find lower levels of physical activity are associated with attrition. It is worth noting, however, that two of these identified studies (Clarke et al., 1996 and Busetto et al., 2009) required individuals to participate in exercise which may have deterred individuals with lower baseline levels of physical activity, thus, resulting in a biased sample. We reflect the findings of the majority of studies considering an association between physical activity and attrition, observing no significant association between the variables.

This finding may be explained by our measurement of physical activity. Our hypothesis is based on the assumption of a deliberate and purposeful engagement in physical activity as an indicator for self-discipline. The methodology we utilise is, however, a validated method for the assessment of total energy expenditure rather than a specific assessment of engagement in exercise activities, such as attendance to a gym. It is suggested that our elicitation of physical activity is not a robust proxy for self-discipline and, therefore, the resulting analysis does not fully assess the proposed hypothesis. This is reflected in Teixeira et al. (2004) who find a significant association between physical activity and attrition when defining physical activity as the number of minutes of exercise per day, but no significant association when physical activity is defined as daily energy expenditure (kj/day).

3.4.13: Alcohol

A further health behaviour in which we find no evidence of association with attrition is risky alcohol consumption. This finding is consistent with the past literature in which all studies examining this association find no significant relationship (Inelmen et al. (2005), Clark et al. (1996), Fabricatore et al. (2009) and Brownell, Heckerman and Westlake (1979)).

One explanation for the non-significant findings of perception of diet, physical activity and risky alcohol consumption may be the misplaced assumption that self-efficacy predicts both healthy change behaviours (e.g. weight loss) and static measures of health (e.g. weight status). Self-efficacy is a measure of an individual's perception of their ability to demonstrate the behaviours necessary to achieve successful outcomes. This may be, for example, an individual's perception of their ability to adhere to recommendations of healthy eating and physical activity. Several of the most established behaviour change theories (the Health Belief Model, the Theory of Planned Behaviour, the Social Cognitive Theory and, therefore, the COM-B model of behaviour change) outline self-efficacy as a key driver of change. Understandably, an individual's perceived belief in their ability to change is likely to directly affect actual change. Thus, in our research, an individual's level of self-efficacy is likely to directly affect attrition. The association between self-efficacy and health status is less direct and, thus, less predictable. Clum et al. (2014) unexpectedly find a positive association between self-efficacy and BMI status (i.e. higher self-efficacy is associated with higher BMI) evidencing the more complex relationship between these variables. The potential incorrect assumption may partly explain our lack of significant findings, although it is likely that the relationship is more complex beyond just this single factor.

3.4.14: Initial Weight Loss

Previous discussions regarding efficacy expectations (i.e. one's perceived ability to change behaviour) should not be confused with outcomes expectancies (i.e. the outcomes one expects from behaviour change). In the previous chapter we discussed the hypothesised importance of outcome expectancies on the observed association between initial weight loss and overall weight loss. This hypothesis was based on the assumption that initial weight loss provided increased motivation for continued weight loss. Similar hypotheses can be made regarding attrition i.e. greater initial weight loss provides increased motivation for continued engagement, thus, is associated with increased retention.

The findings from past research are consistent and robust. Individuals with worse initial weight outcomes (low weight loss, no weight change or weight gain) are more likely to drop out of treatment (Mitchell and Stuart, 1984, Greenburg et al., 2009, Fabricator et al., 2009, Packianathan et al. 2005, Brownell et al. 1979, Colombo et al., 2014, Ortner-Hadžiabdić et al., 2014 and O'Leary, 2012). We also find a relationship between greater initial weight loss and engagement to the later stages of the weight management service. The coefficient for week ten engagement is -0.11 (p-value=<0.01) and the coefficient for week twelve is -0.09 (p-value=<0.01). The average weight loss at week two is 3.25kg. Individuals losing more than 3.25kg, on average, attended until week 11. Individuals losing less than 3.25kg, on average, attended to week 9. This two week difference may seem small, however, as a proportion of the total sessions this difference is significant. It both increases individual's exposure to weight management recommendations and engages individuals to the critical point of weight management, discussed previously.

This finding does not, however, prove the hypothesis presented previously. An alternative hypothesis is that initial weight and attrition are both a result of pre-existing low motivation. This hypothesis is theoretically supported by the Health Belief Model which proposes that individuals are less likely to make positive behaviour changes if pre-existing beliefs about the benefits of change are low. Similarly, the Theory of Planned Behaviour proposes that an individual's attitude toward behaviour change will partly determine his or her participation. This hypothesis is based on the assumption that pre-existing levels of motivation determine both weight loss and attendance. Considering findings from past research we find some evidence (Huisman et al., 2010 and Prochaska et al., 1992) of an association between pre-treatment measures of motivation and attrition although the amalgamated findings are largely inconclusive (Moroshko, Brennan and O'Brien, 2011).

The first hypothesis is based on the assumption that initial weight loss is a motivating factor. Related to this assumption is the effect of weight loss expectancies on attrition. If individuals have unrealistic weight loss expectations they may be inclined to drop out of treatment, if these expectations are not being met. This hypothesis also is theoretical underpinned by the Health Belief Model. Poor initial treatment response may increase perceived barriers to achieving outcomes and may decrease the perceived benefits of engagement. Similarly, within the Theory of Planned Behaviour, poor initial response to treatment may result in an increasing negative attitude towards the evaluation of one's self performance and a decreasing sense of perceived behavioural control (see the previous chapter for discussion regarding Locus of Control). Previous studies of outcome expectancies and attrition provide relatively strong evidence for an association between unrealistic or high expectations and attrition (Moroshko, Brennan and O'Brien, 2011).

Further, Grave et al. (2005) present the results of a survey collecting self-reported reasons for attrition from obesity treatment. "*Unsatisfied with weight loss*", was reported by 49% of individuals and was the fifth most reported reason for drop out. These findings provide support for the hypothesis that poor initial weight loss outcomes result in subsequent attrition.

3.4.15: Consistency of Attendance

The two hypotheses of the association between attrition and initial weight loss may also explain the association between attrition and the consistency of attendance. Consistency of attendance and attrition may both be a result of pre-existing low motivation or, consistency of attendance influences the duration of engagement i.e. consistent exposure to the sessions encourages attendance to the later stages of the programme. No previous research has considered the effect of consistency of attendance on attrition

We find consistent attendance to be associated with retention. Individuals who attend consistently are more likely to be engaged at week twelve compared to individuals who attended inconsistently. The coefficient is 0.32 (p-value=<0.01). Sixty-one percent of individuals who consistently attended the sessions were engaged at week twelve compared to only 48% of those who attended inconsistently.

3.4.16: Self-Referral

Central to the discussions regarding initial weight loss and the consistency of attendance is the concept of pre-treatment motivation. In the previous chapter we suggested that referral type may be an indicator of motivation, where individuals choosing to self-refer exhibit higher self-motivation. We have previously outlined past literature examining the association between self-motivation and attrition and found, overall, little conclusiveness.

A further study does, however, specifically explore the association between referral type and attrition. Colombo et al. (2014) find individuals referred by a physician are more likely to complete (defined as engagement at 6 months) than those referred by friends/family or with no referral (attrition rates: 48% and 64% respectively). This finding is in contrast to the hypothesis that self-referred individuals are more likely to adhere to treatment. In past discussions we have suggested that medical referrals may provide a further incentive to attend due to increased salience of the necessity to lose weight and an increased perception of seriousness. This hypothesis is supported by the findings of Gill et al. (2012) who find a much higher attrition rate within a medical setting (53.9%) compared to, an arguably more clinical, surgical setting (11.9%). Interestingly, our findings support neither hypothesis, as we find no evidence of an association between referral type and attrition when defined as drop-out from the service. We do, however, find evidence of an association between self-referral and starting the service. We find individuals who self-refer are more likely to start the service compared to those referred by a health professional. The estimated coefficient is relatively small (β=0.19, p-value=<0.01) with 75.3% of individuals self-referring compared to only 70.3% of individual referred by a health professional. Whilst our finding contrasts with the findings of Colombo et al. (2014), it is supported by the previously discussed hypothesised theoretical relationship of self-referral as a proxy indicator of motivation. Further, under the assumption that motivation is time limited, we can also begin to build a hypothesis of why referral type is found to be significant in the earlier stages of the programme but not in the latter. If self-referral is a proxy for higher motivation to change at time of referral we are more likely to see significant effects in measure of attrition closer to this event than in stages of programme temporally distant.

3.4.17: Time

In the previous chapter it was suggested that the association between the variables concerning time between stages of the programme and weight loss may be influenced by (1) pre-existing motivation or (2) changes in motivation across time periods. The same hypotheses are proposed for the association between these variables and attrition and, as such, are;

(1) Motivation to change is greatest at referral and decreases with time, thus, the longer the period of time between referral and treatment, the higher the probability of attrition.

(2) Motivation is stable across time. Times between stages of the programme and attrition are products of pre-existing motivation. Low motivation results in both an increased period of time to the start of treatment and an increased probability of attrition.

No existing research on the effect of time on attrition exists.

We find a significant association between the number of days between registration and starting the programme and attrition at both week ten and week twelve. The coefficients are -0.01 (p-value=0.01) and -0.01 (p-value=0.01) respectively. Whilst significant, the difference between the two groups is minimal. Individuals who dropped out prior to week 10 took, on average, 14 days to start the service after registering compared to an average of

13 days for those engaged at week 10. Individuals who dropped out prior to the final week took, on average, 14 days compared to an average of 12 days for those engaged at week 12.

3.4.18: Depression

Low motivation is a well-documented symptom of depression and depression is relatively consistently linked to attrition. Five studies have been identified reporting a positive relationship between attrition and depression[40] i.e. higher depression increases the probability of attrition.

Markowitz et al. (2008) supports our previous suggestion that depression may decrease an individual's motivation to engage. Further, they suggest the probability of attrition may also be increased due to a tendency for depressed individuals to amplify physical symptoms of chronic medical conditions (Katon and Ciechanowski, 2002). This introduces increased perceived barriers to participation, thus, reducing the probability of adherence to treatment. Further, returning to discussions regarding support Markowitz et al. (2008) finds that depressed individuals often have decreased levels of social support which in previous discussions has been hypothesised to cause attrition from weight loss programmes.

Our results are consistent with previous studies as we find a negative association between the presence of depression and engagement at week ten. The coefficient is -0.24 (p-value=0.05). The difference between the two groups is relatively large, whereby, 66% of individuals with depression are engaged at week 10 compared to 72% of non-depressed individuals.

[40] Pekarik et al. (1984), Change, Brown and Nitzke (2009), Clark et al. (1996), Trief et al., (2014) and Fabricatore et al. (2009).

3.4.19: Stress

Past studies examining the association between stress and attrition have mixed overall findings. Equal numbers of studies have found an association between higher (Chang, Brown and Nitzke., 2009 and Michelini et al., 2014) and lower (Fabricatore et al., 2009 and Yass-Reed, Barry and Dacey, 1993) levels of stress and attrition. These mixed findings maybe a result of the heterogeneity of the methodologies utilised to assess stress. Each study takes a different approach, namely measurement of; perceived stress, measured signs of stress, a binary self-reported measure of experienced stress in the previous six months and a self-reported measure of expected stress (Chang, Brown and Nitzke., 2009, Michelini et al., 2014, Fabricatore et al., 2009 and Yass-Reed, Barry and Dacey, 1993, respectively).

The positive association between stress and attrition is theoretically supported by the Health Belief Model. Individuals scoring highly on pre-treatment measures of current stress may find adhering to weight management programmes difficult due to increased perceived barriers to participation resulting from factors contributing to current stress levels. In a survey of self-reported reasons for attrition "*Work problems*" and "*Family problems*" were reported by 51% and 54% of individuals respectively (Grave et al., 2006). Clearly, stressful factors likely increase pre-treatment measures of stress are associated with attrition.

Yass-Reed, Barry and Dacey (1993), however, measure expected stress. It is hypothesised that the negative relationship observed in this study may be due to the more realistic or overestimated expectations of the individuals reporting high expected stress. These individuals will subsequently be more prepared for the stress-related effects of weight management including the opportunity to prepare coping strategies. This hypothesis is supported by previous discussion, both in this chapter and the previous chapter, of outcomes expectancies and coping mechanisms.

The methodology utilised in our study is a binary measure of stress, assessed by a healthcare professional. We, however, find no significant association between stress and attrition at either stage of the service.

3.4.20: Initial BMI

A further variable whereby the hypothesised relationship with attrition is underpinned by the Health Belief Model is initial BMI. Firstly, a higher BMI may increase an individual's perception of the severity of obesity, as the risk of developing co-morbidities increases with weight. Secondly, higher BMI may increase the perceived benefits of losing weight, in the alleviation or avoidance of co-morbidities. Thirdly, evidence suggests initial BMI may act as a prompt or "cue to action" for weight loss (see the previous chapter for a full account of these hypotheses).

A further hypothesis, specific to the relationship with attrition, is that a lower initial BMI may result in the achievement of desired weight loss earlier in the programme, thus, increasing the probability of attrition from the service.

A substantial quantity of past research exists exploring the relationship between initial weight status and attrition. In total, twenty-nine studies have been identified with, overall, mixed findings. We find individuals with a higher initial BMI are more likely to engage to week 12 of the programme. The coefficient is 0.03 (p-value=0.01). The difference between the two groups is minimal; individuals engaged at week twelve had an average initial BMI of 36 compared to an average BMI of 35 for those who started the service but dropped out prior to the final week. A two sample t-test for comparing means, however, finds this difference to be significant; t=-1.93 (p-value=0.05).

3.4.21: Deprivation

As a construct of many of the variables discussed in the chapter, hypotheses regarding an association between deprivation and attrition are complex. Previous literature exploring socioeconomic status and attrition have largely found no significant association[41], although one study finds lower socioeconomic status to be linked to attrition (Bennett and Jones, 1986). The deprivation scores, which in turn transform into the deprivation declines used within our analyses, are derived from a range of variables[42] which have considerable overlap with traditional socioeconomic variables. Measures of deprivation, however, encompass a broader range of constructs reflective of living standard. No previous studies have been identified specifically examining the association between deprivation and attrition.

There is a relatively robust evidence base examining population prevalence of ill-health in relation to deprivation. Considering attrition, however, little evidence exists examining an association between attrition from public health programmes and deprivation. Further, of the available studies, overall findings are mixed. Lowey et al. (2002), for example, find no evidence of an association between smoking cessation and deprivation. Self et al. (2005) and Grant et al. (2012), however, find evidence of a positive association between

[41] Pekarik et al (1984), Mitchell and Stuart (1984) and Graffagnino et al (2006).
[42] Income, Employment, Health deprivation and Disability, Education Skills and Training, Barriers to Housing and Services, Crime and Living Environment.

deprivation and attrition from Cognitive Behavioural Therapy (CBT), a treatment for mental health conditions. It is, therefore, difficult to form a hypothesis based on past literature due to the lack of research and lack of relevant research.

Previous hypotheses regarding the relationship between deprivation and weight loss proposed that probability of success may be lower for more deprived individuals due to associations between deprivation and factors found to increase attrition rates, (specifically; emotional problem solving, lower perception of control and actual control). We may hypothesise, therefore, a positive relationship between attrition and deprivation. We, however, find no significant association between the variables.

3.4.22: Gender

The results of two final variables explored in this chapter are now presented. They are gender and ethnicity. In the previous chapter we suggested that male individuals who engage in weight management activities represent a sub population of males most likely to succeed, due to high self-motivation and high perception of risk. Generally previous studies have found no significant association between gender and attrition; however, those that do find males are more likely to adhere to treatment programmes. We reflect the findings of the majority of studies, finding no significant association between gender and attrition within the weight management service. We do, however, observe a negative significant association between registering for the service and being male i.e. males are significantly less likely to register than females (β=-0.40, p-value0.00). Eighty-three percent of females contact to register compared to only 70.4% of males. This supports previous discussions which proposed that male participating in the weight management service represent a motivated, and thus more probable to succeed, sub-set of the larger male population.

3.4.23: Ethnicity

The theoretical association between ethnicity and attrition is unclear. There is evidence of differing obesity prevalence amongst different ethnicities; however, no clear pattern exists when factoring in further variables such as gender and age (see previous chapter).

Osei-Assibey et al. (2010) suggests three possible explanations for higher obesity prevalence observed in some ethic groups in the USA. These hypotheses also hold for UK findings. (1) Adaptation to obesity-related aspects of typically western lifestyles, such as, relative physical inactivity and relatively high fat and high sugar diets. (2) Physiological differences in some ethic groups resulting in a tendency for weight gain. (3) Typically “obesity tolerant” cultural influences and attitudes, such as, lower levels of body dissatisfaction even when obese.

In the limited literature on ethnicity and attrition from weight management, two studies from the USA found a positive association between being non-white or African American individuals and attrition (Graffagnino et al., 2006 and Fowler et al., 1985), however, two further studies from the USA find no significant association (Chang, Brown and Nitzke, 2009 and Fabricatore et al., 2009). The hypotheses made by Osei-Assibey et al. (2010) may provide explanations for the significant findings, although they are more likely to affect weight and weight loss than attrition. We find no evidence of an association between ethnicity and attrition.

3.4.24: Missing Data

Before concluding this Chapter we briefly present our acknowledgement of the issues of missing data within our research. As presented in Chapter 2, missing data represents <2% of the data points within our dataset, however, because regression analyses exclude an individual if any data point is missing, this results in the exclusion of 26% of individuals. We previously present evidence that the mechanism under which the missing data occurs is missing at Random (MAR) and, thus, that the sample utilised within our analyses is likely to be an unbiased sub-set of the original complete dataset. Whilst we find little to no evidence for the presence of variables which are not missing at random (NMAR), we do observe several variables exhibiting a significant relationship with engagement at week 10 and attendance at week 12 which strongly suggests that attrition is much more of an issue than missing data within our research.

3.5: Conclusion

Overall, significant relationships were found between attrition and having children, initial BMI, initial weight loss, time between registration and starting, smoking, diabetes and depression. Initial weight loss and time between stages of the programme seem to provide the best predictors of attrition. For week ten outcomes, it is further suggested that depression exhibits a relatively strong positive relationship and smoking and consistent attendance exhibit a relatively strong negative relationship with attrition.

As per Chapter 2, the discussion present the results of analyses in the context of the current available literature and have focused on the main objective of the research which is how the evidence presented in this thesis supports the continuous improvement of weight management services. Again, reflecting back to discussion with Chapter 1 it is strongly acknowledged that the evidence presented here has much wider implications in the contexts of complex systems thinking, health inequalities and in the political environment. Whilst variables, such as, initial weight loss and time between registration and starting have implications for service delivery, the significant findings of relationships between children and depression and attrition, in particular, has much broader implications. As previously stated, we have chosen not to present individual discussions regarding the broader implications of the research within disparate sections of individual chapters but rather to acknowledge their importance and, thus, dedicate a comprehensive and more appropriately extensive discussion within Chapter 6.

The chapter has presented the determinants of attrition for individuals engaged at the later stages of the programme. The following chapter revisits the weight loss outcomes presented in the previous chapter but, this time, controls for sample selection.

Chapter 4

Factors associated with weight outcomes controlling for sample selection:

Evidence from a publically funded weight management programme

4.1: Justification

Attrition is a recognised problem in weight management research as evidenced in Chapter 3. Currently, within the previous literature, two broad methods have been adopted to deal with attrition issues. These are (1) excluding drop-outs from analyses or (2) imputation methods. The research presented thus far in this thesis has adopted the first, exclusionary, method[43] in Chapter 2, whilst commenting on and presenting evidence of the potential biases of this method in Chapter 3. This method is relatively standard amongst weight management intervention research with examples of several studies utilising this approach.[44]

The current popular alternative, the use of imputation methods, have also been utilised by a number of studies.[45] The most common approach is the LOCF method whereby the last weight recorded is used in place of later missing weight records. This method is attractive as it is computational simple, can provide a conservative estimate of the treatment effect and is less extreme than the exclusionary method described above (Gadbury, Coffey and Allison, 2003). The method is, however, criticised due the assumption that an individual's weight remains constant post attendance, thus, underestimating the true variability in the data (Jørgensen et al., 2014). Whilst attending a weight management service, an individual's weight trajectory may be declining and we may be inclined to assume a continuation of this trend, however, research has shown that many individuals regain previously lost weight, post attendance (Barte et al., 2010). A further imputation option is, thus, the BOCF method which assumes individuals regain weight back to the baseline post attendance. In both

[43] Whereby, non-attendance to week 10 and 12 of the service results in these individuals being excluded from analyses of weight loss outcomes.
[44] Truby et al. (2006), Handjieva-Darlenska et al. (2012) and Heska et al. (2003).
[45] Teixeira et al. (2004); Jebb et al. (2011) and Womble et al. (2004).

approaches there is overconfidence in the precision of the imputed data which inevitably casts doubts on the resulting estimated effects and interpretations (Jørgensen et al., 2014). Multiple imputation methods are less frequently utilised in the literature but, to some extent, address this problem. With multiple imputation, each missing value is replaced by two or more imputed values to reflect aforementioned uncertainties (Rubin, 1996). With all imputation methods a critical assumption is, however, that attrition occurs at random i.e. there is an assumption that missing data values carry no information about probabilities of 'missingness' (Rubin, 1996). Whilst mathematical convenient, this chapter aims to test this assumption, utilising statistics methods to detect non-random sample attrition.

The method we utilise in this chapter is the Full Information Maximum Likelihood (FIML) estimation. FIML is a two part model; (1) the main regression equation which estimates the weight loss outcomes and (2) the selection equation which estimates engagement at week ten or twelve. The method first tests for correlation between the error terms of the two equations. If no correlation is detected we can conclude that the results from regressions presented in Chapter 2 are unbiased. If we detect correlation, however, this suggests an unobserved variable(s) is significant to both engagement and weight loss outcomes, thus, attrition is non-random and results of previous regressions are biased. If correlation is detected the method uses information from those individuals who did not engage at weeks ten or twelve to correct the estimates of the parameters in the regression model. This method is preferable to those described previously as it gives unbiased parameter estimates and standard errors and does not require the careful selection of values to replace missing data involved in multiple imputation methods. Due to computational complexities this method is not widely used within current literature despite offering a preferable alternative to methods previously described. This Chapter, therefore, presents some of the first research into weight management interventions to report outcomes through the utilisation of maximum likelihood sample-selection methods.

4.2: Introduction

This chapter will test for evidence of non-random attrition into the latter stages of the weight management service where weight outcomes are recorded. We utilise methods by which to correct for any detected bias utilising information from all individuals who start the service.

4.3: Programme description and variables explored

The data used in this Chapter is from the weight management programme previously analysed in Chapters 2 and 3 and is described in detail in Appendix 10.

4.4: Method

The method utilised is FIML estimation. The FIML approach involves a primary regression equation and a probit selection equation which controls for the sample selection mechanism. Specifically, the probability of engagement at week ten and week twelve is estimated using data from all individuals starting the service. This conditional probability is then applied as a correction in the main equation exploring weight outcomes.

Whilst we employ the FIML method, the discussion below, adapted from Greene (2007), illustrates the problem of sample selection bias using the two-step Limited Information Maximum Likelihood (LIML) method. Asymptotically, these two methods are equivalent; however, the FIML method estimates the two equations simultaneously producing the correct standard errors and recovers the structural parameters.

Heckman's sample selection model is based on the following two latent variable models:

$$Y_1 = \beta' X + U_1 \tag{1}$$

$$Y_2 = \gamma' Z + U_2 \tag{2}$$

Where X and Z are vectors of regressors and U_1 and U_2 are the error terms. U_1 and U_2 are, conditional on X and Z, jointly normally distributed with zero mean. Equation (1) is the main equation of interest, in this case, weight outcomes. Equation (2) is the selection equation i.e. the probability of whether an individual attends the latter sessions of the weight management service. $Y_2 = 1$ if we observe Y_1 and zero otherwise. We assume the vector Z contains all variables in the vector X and that we observe Z (and thus X), regardless of whether we observe Y_1.

In previous chapters we have outlined a non-negligible proportion of individuals who start the weight management service but who are not engaged in the latter stages (weeks 10 and 12). For these individuals, there is no information on weight outcomes, and so the corresponding observations cannot be used when estimating the weight outcome equations in Chapter 2 due to missing values for the dependent variable. We may have estimated these equations based on a non-random sample of individuals, thus, introducing selectivity bias.

4.4.1: Demonstrating Sample Selection Bias

As previously stated, we apply the following assumptions:

(i) Z and X are always observed, but Y_1 is only observed if $Y_2 = 1$.

(ii) The exogeneity of X and Z.

(iii) The joint normality of the error terms U_2 and U_1.

Assumption (iii) thus implies that:

$$E(U_1|U_2) = \rho U_2 \qquad (3)$$

Where ρ measures the covariance between U_1 and U_2.

In our model, sample selection bias arises when the residual in the selection equation (i.e. U_2) is correlated with the residual in the primary equation (i.e. U_1), i.e. whenever $\rho \neq 0$. To demonstration this we first derive the expression for $E(Y_1|Z, Y_2 = 1)$ i.e. the expectation of the weight outcome variable conditional on observable variables Z and selection into weeks 10 and 12 of the service.

We begin by deriving $E(Y_1|Z,U_2)$:

$$E(Y_1|Z,U_2) = \beta' X + E(U_1|Z,U_2) \quad (4)$$

Utilising the exogeneity assumption (ii) we can write this expression as:

$$E(Y_1|Z,U_2) = \beta' X + E(U_1|U_2) \quad (5)$$

And further, assuming bivariate normality (iii) we can write the expression as:

$$E(Y_1|Z,U_2) = \beta' X + \rho U_2 \quad (6)$$

Since we can't condition on unobservable variables (i.e. U_2) equation (6) is not directly usable in applied work. To obtain an expression for the expected value of Y_1 conditional on observables Z and the selection outcome Y_2, we make use of the law of iterated expectations:

$$E(Y_1|Z,Y_2) = E[E(Y_1|Z,U_2)|Z,Y_2] \quad (7)$$

Using equation (6):

$$E(Y_1|Z,Y_2) = E[\beta' X + \rho U_2|Z,Y_2] \quad (8)$$

$$= \beta' X + \rho E(U_2|Z,Y_2) \quad (9)$$

$$= \beta' X + \rho h(Z,Y_2) \quad (10)$$

Where $h(Z,Y_2) = E(U_2|Z,Y_2)$ is some function.

Because we are looking at the weight outcomes of individuals conditional on engagement at week 10 and 12 (i.e. Y_2 = 1), we only need to find $h(Z, Y_2 = 1)$. Our model and assumption implies:

$$E(U_2|Z, Y_2 = 1) = E(U_2|U_2 \geq -\gamma' Z) \tag{11}$$

Using the assumption that U_2 follows a normal distribution with mean zero and variance equal to 1 then:

$$E(U_2|U_2 > c) = \frac{\phi(c)}{1 - \Phi(c)} \tag{12}$$

Where c is a constant, ϕ denotes the standard normal probability density, and Φ is the standard normal cumulative density. Thus,

$$E(U_2|U_2 > -\gamma' Z) = \frac{\phi(-\gamma' Z)}{1 - \Phi(-\gamma' Z)} \tag{13}$$

$$E(U_2|U_2 > -\gamma' Z) = \frac{\phi(\gamma' Z)}{\Phi(\gamma' Z)} \equiv \lambda(\gamma' Z) \tag{14}$$

Where λ(.) is the inverse Mills ratio.

The fully parametric expression for the expected value of Y_1, conditional on observable variables Z and selection in weeks 10 and 12 of the service (Y_2 = 1) is therefore:

$$E(Y_1|Z, Y_2 = 1) = \beta' X + \rho\lambda(\gamma' Z) \tag{15}$$

4.4.2: Exogenous Sample Selection

In this section we assume that unobservable variables determining engagement in weeks 10 and 12 of the service (captured in the error term U_2) are independent of the unobservable variables determining weight outcomes (captured in U_1):

$$E(U_1|U_2) = 0 \tag{16}$$

When the covariance between U_1 and U_2 equals zero (i.e. ρ = 0) we can estimate weight outcomes using OLS (as presented in Chapter 2) since:

$$E(Y_1|Z, Y_2 = 1) = \beta' X \tag{17}$$

Hence

$$E(Y_1|Z, Y_2 = 1) = \beta' X + \varsigma_1 \tag{18}$$

Where ς_1 is a mean-zero residual that is uncorrelated with X.

4.4.3: Endogenous Sample Selection

Sample selection bias occurs when the error terms of the main and selection equations (U_1 and U_2) are correlated (i.e. $\rho \neq 0$). Equation (15) demonstrates that the expected value of Y_1, conditional on Z and Y_2 = 1, is equal to $\beta' X$, plus an additional term which is the product of the covariance of the error terms (ρ) and the inverse Mills ratio evaluated at $\gamma' Z$. Therefore in the sample of individuals engaged at weeks 10 and 12, actual Y_1 is written as the sum of expected Y_1 (conditional on Z and selection) and a mean-zero residual:

$$E(Y_1|Z, Y_2 = 1) = \beta' X + \rho\lambda(\gamma' Z) + \varsigma_1 \tag{19}$$

Given equation (19) and that $\rho \neq 0$, if we were to run an OLS regression with weight outcomes (Y_1) as the dependent variable with explanatory variables X, then $\rho\lambda(\gamma'Z)$ would end up in the residual and the resulting estimates will be biased.

4.4.4: Correction with the Heckman Method

If we had data on $\lambda(\gamma'Z)$ we could simply add this variable to the model and estimate it using OLS. In practice, however, we do not have direct data on $\lambda(\gamma'Z)$ but, as we assume the functional form of $\lambda(.)$ and Z is observed, the only missing ingredient is the parameter γ which can be estimated using a probit model. The Heckman method, therefore, can be represented by a two-step estimation technique whereby we, first, use all observations for individuals who started the service and estimate a probit model where Y_2 is the dependant variable and Z are the explanatory variables. Based on the parameter estimates ($\hat{\gamma}$) we calculate the inverse Mills ratio for each observation:

$$\lambda(\hat{\gamma}Z) = \frac{\phi(\hat{\gamma}'Z)}{\Phi(\hat{\gamma}'Z)} \tag{20}$$

Secondly using the weight outcome observations for individuals who selected into week 10 and 12, we run an OLS regression where Y_1 is the dependant variable and X and $\lambda(\gamma'Z)$ are the explanatory variables.

$$Y_1 = \beta'X + \rho\lambda(\gamma'Z) + \varsigma_1 \tag{21}$$

This will give consistent estimates of the parameter vector β, i.e. by including the inverse Mills ratio as an additional explanatory variable, we have corrected for sample selection bias.

In addition to the two equations, when using the Heckman command in Stata, we are provided with an estimate of ρ (the correlation of the residuals in the two equations) and a likelihood ratio test of ρ = 0. Under the null hypothesis there is no sample selection bias (i.e. ρ = 0). If we cannot reject the null hypothesis this indicates the presence of sample selection bias and, thus, the requirement to correct for this bias using the method outlined above.

4.4.5: Partial Effects

The effect of a change in X_k on expected Y_1 is expressed as:

$$\frac{\partial E(Y_1|\beta' X)}{\partial X_k} = \beta_k \tag{22}$$

For example, if X_k is age and Y_1 is the weight outcome, then β_k measures the marginal effect of age on expected weight outcomes in the population.

The effect of a change in x_k on expected Y_1 for individuals in the population for whom Y_1 is observed:

$$\frac{\partial E(Y_1|\beta' X, Y_2 = 1)}{\partial x_k} = \beta_k + \rho \frac{\partial \lambda(\hat{\gamma}' X)}{\partial x_{ki}} \tag{23}$$

If:

$$\lambda' c = -\lambda[c + \lambda(c)], \tag{24}$$

Then:

$$\frac{\partial E(Y_1|\beta' X, Y_2 = 1)}{\partial x_k} = \beta_k + \rho \gamma_k \lambda(\hat{\gamma}' X + \lambda(\hat{\gamma}' X)] \tag{25}$$

It can be shown that $c + \lambda(c) > 0$, and so if ρ and γ_k have the same sign, the partial effect in the sample is lower than that on expected Y_1, in the population.

4.4.6: Non-Continuous Outcome Variables

The above outlines a method for controlling for sample selection when the outcome variable in the main equation is continuous. We also observe non-continuous outcome variables in the form of significant weight change, a binary variable which equals 1 when an individual loses over 5% of their initial body weight, and zero otherwise. This example can be written as:

$$Y_1 = 1[\beta' X + U_1 > 0] \tag{26}$$

$$Y_2 = 1[\gamma' Z + U_2 > 0] \tag{27}$$

Where Y_1 is observed only is $Y_2 = 1$ and Z contains X. Again, probit estimation of β on only individuals engaged at week 10 or 12 may lead to inconsistent results, unless U_1 and U_2 are uncorrelated. A similar two stage procedure can be applied to correct for sample selection bias. Firstly, we obtain $\hat{\gamma}$ by estimating the participation equation using a probit model. Construct $\widehat{\lambda}_2 = \lambda(\hat{\gamma}' Z)$. Secondly, estimate the equation using probit estimation, with $\hat{\lambda}_2$ added to the set of regressors:

$$\Pr(Y_1 = 1 | X, Y_1 = 1) = \Phi(\beta' X + \rho\,\widehat{\lambda}_2) \tag{28}$$

Where ρ measures the correlation between the residuals U_1 and U_2. Again, using Stata's heckprob command we gain both estimates of ρ and a likelihood ratio test of $\rho = 0$.

The discussions above describe the Heckman two-step LIML procedure for controlling for sample selection bias. In this Chapter we utilise the FIML method. As previously stated, these two methods are equivalent; the FIML method estimates the two equations simultaneously producing the correct standard errors and recovers the structural parameters. Comparisons of the two-step LIML procedure and the FIML method are discussed further in section 4.6.

4.5: Identification Strategy

A prevalent discussion in the literature regarding the use of sample selection models is the potential problem of multicollinearity and the resulting consequences for model estimates that arise from the inclusion of the inverse Mills ratio (Bushway et al., 2007). The inverse Mills ratio is estimated by a non-linear probit model, thus, theoretically it will not be perfectly correlated with *X* (the vector of regressors in the main equation, see Equation 1), even if the same variables are used within the selection equation and the main equation. If the first (selection) stage was linear, the model would not be identified and could not be estimated (Bushway et al., 2007). The probit model is, however, approximately linear over the mid-range values and, therefore, is only truly non-linear when inverse Mills ration (λ, see Equation 14) takes on extreme values (see Figure 4.1), hence researchers frequently report high correlations between the λ and *X*, inflated standard errors and problems of multicollinearity (Puhani, 2000).

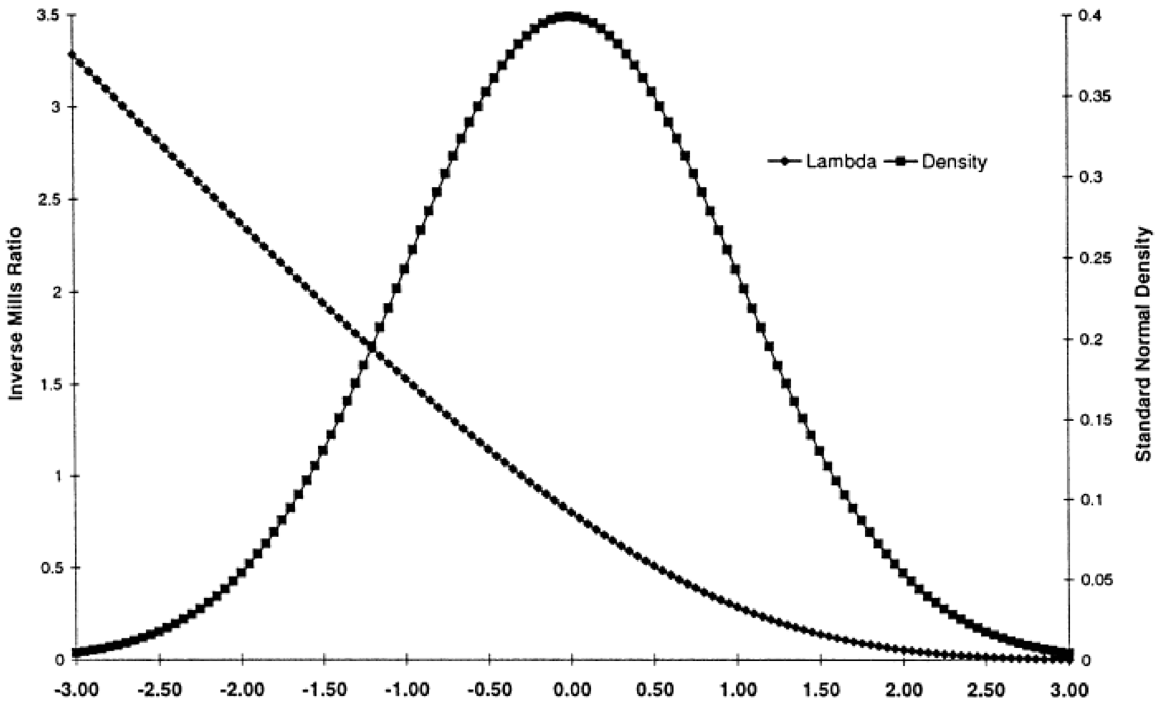


Figure 4.1: The quasi-linearity of the inverse mills ratio (Puhani, 2000).

A common solution to this issue is to incorporate exclusion restrictions. In practice this involves the identification of a variable which directly effects selection but not the outcome variable in the main equation, and the inclusion of this variable in *Y* (the vector of regressors in the selection equation, see Equation 2) but not in *Z* (Puhani, 2000). Unfortunately, it is often very difficult to identify variables that meet the criteria by which it may be utilised as an exclusionary restriction due to the requirement for convincing theoretical justifications that ensures the selection process has been accurately modelled (Puhani, 2000 and Bushway et al., 2007). Further, even when a suitable variable is identified there are often substantive limitations, such collection of or access to the required data.

As a result it is relatively common to find examples of research which does not incorporate exclusion restrictions. The research presented in this chapter is an example. Due to the complexity of the factors effecting weight loss and attrition, a variable which theoretically only affects one but not the other is difficult to identify. We previously present the example of 'distance from the weight management service' which, at first glance, may seem to meet the exclusionary criteria. As previously outlined, however, due to the geographical prevalence of groups, one may easily hypothesise that increased distance from a group may also reflect increased distance from food environments and physical activity opportunities which will also directly affect weight loss. In our research, we do not identify a valid exclusion restriction but still estimate the model. As the model is theoretically sound, the potential problem is a numerical one. We estimate the model in acknowledgement of the potential problem and allow for careful interpretation of results.

4.6: Literature Review

Selection models are increasingly being used within social science and economics research. Their use in the field of obesity research is, however, limited. Existing examples include research utilising secondary data analysis where there is a requirement to control for selection into longitudinal studies (for example, Basu et al., 2013 and Wang et al., 2002) and the effect of obesity on entrance and financial performance in the labour market whereby individuals not in employment are not observed thus biasing samples (see, for example, Reichert and Tauchmann, 2014, Sullivan, Ghushchyan and Ben-Joseph., 2008 and Brown 2011). Such research, whilst of interest, does not reflect the objective of this thesis which aims to evaluate the true effectiveness of weight management programmes by controlling for individuals who drop-out prior to completion.

Four studies have been identified which utilise sample selection models to evaluate the outcomes of weight management interventions. Three of these studies rely on data from the same intervention; a financial incentive scheme for weight loss (Augurzky et al., 2012; Augurzky et al., 2015 and Reichert and Tauchmann, 2014). The remaining study explores the effect of social networking on weight loss (Poncela-Casasnovas et al., 2015).

Whilst variables of interest in these previous papers are not comparable to the research presented in this thesis, the necessity of the use of sample selection models is of interest. In particular the paper by Reichert and Tauchmann (2014) compares the outcomes of several estimation methods (OLS, two-step LIML and FIML procedures) using data from a financial incentive scheme for weight loss to assess the requirement for, and effect of using, selection models. From the estimation results the authors conclude that the choice of estimation procedure is clearly important. As previously mentioned the FIML method estimates both the main equation and the selection equation simultaneously producing the correct standard errors and recovering the structural parameters (unlike in the two-step LIML procedure). Numerous simulation studies have demonstrated that, when the assumption that the error terms are bivariate normal is met, the FIML will always be more efficient than the two-step LIML approach (Puhani, 2000).

Reference	Intervention	Sample selection issue	Methods to control for sample selection
Augurzky et al., 2012	RCT testing financial incentives (control, €150 and €300) for weight loss at 4 months.	The success of the treatments is based on individual's provision of weight in the latter stage of the service. Providing a final weigh-in is assumed to be non-random.	(1) Multivariate OLS regressions (2) LIML (3) 'Intention to treat' analysis (4) Treatment effect bounds (Lee, 2009)
Augurzky et al., 2015	Testing the long-term effect of incentives (see Augurzky et al., 2012) at 18 months post payment.	Long-term effect of incentives is based on individual's provision of weight post intervention. Providing a final weigh-in is assumed to be non-random.	(1) Self-reported measured (2) 'Intention to treat' analysis (3) Treatment effect bounds (Lee, 2009)
Poncela-Casasnovas et al., 2015	Exploring the relationship between individual and social networking variable on weight loss.	To estimate weight change two record weigh-in were required. Individuals providing two weigh-ins represent a self-selected and potentially biased sample.	(1) FIML
Reichert and Tauchmann, 2014	To evaluate the effectiveness of financial incentives for weight loss among the obese.	As in Augurzky et al. (2012)	(1) Multivariate OLS regressions (2) LIML (3) FIML

Table 4.1: Literature Summary of Weight Management Programme Research utilising Sample Selection Correction

4.7: Results

The following tables present the results of the FIML estimations controlling for sample selection. The first three tables present the results for (1) percentage weight change, (2) BMI change and (3) significant weight loss at week ten controlling for selection into week ten of the service. The final three tables examine the same weight outcomes at week twelve controlling for selection into week twelve.

Table 4.2: Percentage weight change controlling for sample selection at week 10
Result of the FIML Estimation (all variables, n=1,468)

Variable	Coef.	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
Panel A: Main Equation					
Demographics					
Male	-0.32	0.29	0.27	-0.88	0.25
Age	-0.08	0.04	0.04	-0.15	0.00
Age squared	0.00	0.00	0.15	0.00	0.00
White (ethnicity)	-1.44	0.73	0.05	-2.88	-0.01
Indices of deprivation	-0.04	0.03	0.26	-0.10	0.03
Partner	-0.17	0.17	0.32	-0.51	0.17
Presence of children	0.24	0.23	0.30	-0.21	0.70
Employed	0.29	0.18	0.11	-0.06	0.65
Degree level education	-0.72	0.20	0.00	-1.12	-0.33
Perception of local area	0.00	0.01	0.90	-0.01	0.01
Weight factors					
BMI (initial)	0.05	0.02	0.01	0.01	0.09
Weight change (kg) week 2	0.62	0.04	0.00	0.53	0.70
Aspect of the programme					
Self-referred	-0.31	0.16	0.04	-0.62	-0.01
Days (referral to registration)	-0.01	0.01	0.18	-0.02	0.00
Days (registration to start)	-0.02	0.01	0.05	-0.04	0.00
Consistent attendance	-1.58	0.15	0.00	-1.88	-1.28
Health behaviours					
Smokes	-0.62	0.29	0.03	-1.18	-0.05
Excess alcohol consumption	0.61	0.27	0.03	0.07	1.14
Perception of diet	0.02	0.01	0.00	0.00	0.03
Energy expenditure (kcal/day)	0.00	0.00	0.12	0.00	0.00
Physical health					
Disabled	-0.12	0.37	0.76	-0.85	0.61
Cardiovascular disease	0.16	0.30	0.59	-0.42	0.74
Mobility problems	0.27	0.19	0.16	-0.11	0.64
Diabetes	0.44	0.26	0.09	-0.07	0.94
Hypertension	0.02	0.20	0.93	-0.38	0.41
Mental health					
Depression	0.16	0.28	0.56	-0.39	0.72
Stress	0.03	0.32	0.92	-0.59	0.66
Personality					
Openness	0.00	0.00	0.88	-0.01	0.01
Neuroticism	0.00	0.00	0.70	-0.01	0.01
Conscientiousness	0.00	0.00	0.58	-0.01	0.01
Agreeableness	0.00	0.00	0.80	-0.01	0.01
Extroversion	0.00	0.00	0.25	-0.01	0.00
_cons	-1.67	1.54	0.28	-4.69	1.34

Panel B: Selection Equation					
Demographics					
Male	0.11	0.16	0.49	-0.20	0.43
Age	0.02	0.02	0.25	-0.01	0.06
Age squared	0.00	0.00	0.56	0.00	0.00
White (ethnicity)	0.00	0.33	1.00	-0.65	0.65
Indices of deprivation	-0.02	0.02	0.28	-0.05	0.01
Partner	0.08	0.08	0.36	-0.09	0.24
Presence of children	-0.35	0.11	0.00	-0.57	-0.12
Employed	0.02	0.09	0.85	-0.16	0.19
Degree level education	0.05	0.10	0.64	-0.15	0.25
Perception of local area	0.00	0.00	0.32	0.00	0.01
Weight factors					
BMI (initial)	0.01	0.01	0.14	0.00	0.03
Weight change (kg) week 2	-0.11	0.02	0.00	-0.14	-0.08
Aspect of the programme					
Self-referred	-0.03	0.08	0.66	-0.18	0.12
Days (referral to registration)	0.00	0.00	0.38	0.00	0.01
Days (registration to start)	-0.01	0.00	0.01	-0.02	0.00
Consistent attendance	0.05	0.07	0.51	-0.10	0.20
Health behaviours					
Smokes	-0.28	0.12	0.02	-0.51	-0.05
Excess alcohol consumption	0.15	0.14	0.30	-0.13	0.42
Perception of diet	0.00	0.00	0.06	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.33	0.00	0.00
Physical health					
Disabled	0.34	0.20	0.09	-0.05	0.73
Cardiovascular disease	0.11	0.16	0.52	-0.22	0.43
Mobility problems	0.12	0.10	0.21	-0.07	0.31
Diabetes	0.21	0.14	0.14	-0.07	0.49
Hypertension	-0.07	0.11	0.48	-0.28	0.13
Mental health					
Depression	-0.25	0.12	0.05	-0.49	0.00
Stress	-0.04	0.15	0.80	-0.34	0.26
Personality					
Openness	0.00	0.00	0.82	0.00	0.00
Neuroticism	0.00	0.00	1.00	0.00	0.00
Conscientiousness	0.00	0.00	0.84	0.00	0.00
Agreeableness	0.00	0.00	0.93	0.00	0.00
Extroversion	0.00	0.00	0.49	0.00	0.00
_cons	-0.69	0.65	0.29	-1.96	0.59
ρ	0.16	0.26		-0.35	0.59

Likelihood ratio Test of ρ = 0: chi2(1) = 0.29, p-value = 0.59

Table 4.3: BMI change controlling for sample selection at week 10
Result of the FIML Estimation (all variables, n=1,468)

Variable	Coef.	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
Panel A: Main Equation					
Demographics					
Male	-0.22	0.18	0.24	-0.58	0.14
Age	0.00	0.02	0.89	-0.04	0.05
Age squared	0.00	0.00	0.96	0.00	0.00
White (ethnicity)	-0.59	0.45	0.19	-1.48	0.29
Indices of deprivation	-0.02	0.02	0.24	-0.06	0.02
Partner	0.01	0.11	0.90	-0.20	0.22
Presence of children	-0.08	0.14	0.56	-0.35	0.19
Employed	0.07	0.11	0.55	-0.16	0.29
Degree level education	-0.10	0.13	0.44	-0.35	0.15
Perception of local area	0.00	0.00	0.17	0.00	0.01
Weight factors					
BMI (initial)	-0.03	0.01	0.01	-0.05	-0.01
Weight change (kg) week 2	0.16	0.02	0.00	0.12	0.21
Aspect of the programme					
Self-referred	-0.17	0.10	0.09	-0.36	0.03
Days (referral to registration)	0.00	0.00	0.92	-0.01	0.01
Days (registration to start)	-0.02	0.01	0.00	-0.03	-0.01
Consistent attendance	-0.57	0.10	0.00	-0.76	-0.38
Health behaviours					
Smokes	-0.62	0.17	0.00	-0.96	-0.29
Excess alcohol consumption	0.32	0.17	0.06	-0.02	0.66
Perception of diet	0.01	0.00	0.05	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.65	0.00	0.00
Physical health					
Disabled	-0.05	0.23	0.84	-0.50	0.41
Cardiovascular disease	0.48	0.19	0.01	0.11	0.85
Mobility problems	0.12	0.12	0.33	-0.12	0.35
Diabetes	0.10	0.16	0.54	-0.22	0.42
Hypertension	-0.02	0.13	0.87	-0.27	0.23
Mental health					
Depression	0.03	0.17	0.87	-0.31	0.36
Stress	-0.19	0.20	0.35	-0.58	0.21
Personality					
Openness	0.00	0.00	0.82	0.00	0.00
Neuroticism	0.00	0.00	0.39	0.00	0.01
Conscientiousness	0.00	0.00	0.70	-0.01	0.00
Agreeableness	0.00	0.00	0.87	-0.01	0.01
Extroversion	0.00	0.00	0.06	-0.01	0.00
_cons	-0.44	0.86	0.61	-2.11	1.24

Panel B: Selection Equation					
Demographics					
Male	0.25	0.16	0.11	-0.06	0.56
Age	0.02	0.02	0.35	-0.02	0.05
Age squared	0.00	0.00	0.60	0.00	0.00
White (ethnicity)	0.07	0.32	0.83	-0.56	0.69
Indices of deprivation	-0.01	0.02	0.37	-0.04	0.02
Partner	0.03	0.08	0.73	-0.13	0.18
Presence of children	-0.34	0.11	0.00	-0.55	-0.13
Employed	0.00	0.08	1.00	-0.16	0.16
Degree level education	0.10	0.10	0.28	-0.09	0.30
Perception of local area	0.00	0.00	0.26	0.00	0.01
Weight factors					
BMI (initial)	0.02	0.01	0.06	0.00	0.04
Weight change (kg) week 2	-0.10	0.02	0.00	-0.13	-0.06
Aspect of the programme					
Self-referred	-0.05	0.07	0.45	-0.20	0.09
Days (referral to registration)	0.00	0.00	0.71	-0.01	0.01
Days (registration to start)	-0.01	0.00	0.00	-0.02	0.00
Consistent attendance	-0.02	0.07	0.83	-0.15	0.12
Health behaviours					
Smokes	-0.24	0.12	0.04	-0.46	-0.01
Excess alcohol consumption	0.07	0.13	0.60	-0.19	0.32
Perception of diet	0.00	0.00	0.27	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.14	0.00	0.00
Physical health					
Disabled	0.33	0.19	0.08	-0.04	0.70
Cardiovascular disease	0.19	0.15	0.21	-0.11	0.48
Mobility problems	0.06	0.09	0.52	-0.12	0.24
Diabetes	0.09	0.13	0.50	-0.17	0.35
Hypertension	-0.01	0.10	0.92	-0.20	0.19
Mental health					
Depression	-0.25	0.12	0.03	-0.49	-0.02
Stress	0.05	0.15	0.73	-0.24	0.34
Personality					
Openness	0.00	0.00	0.53	0.00	0.00
Neuroticism	0.00	0.00	0.96	0.00	0.00
Conscientiousness	0.00	0.00	0.68	0.00	0.00
Agreeableness	0.00	0.00	0.87	0.00	0.00
Extroversion	0.00	0.00	0.42	0.00	0.00
_cons	-0.55	0.63	0.38	-1.78	0.67
ρ	0.88	0.02		0.85	0.91

Likelihood ratio Test of ρ = 0: chi2(1) = 144.79, p-value = 0.00

Table 4.4: Significant weight loss controlling for sample selection at week 10
Result of the FIML Estimation (all variables, n=1,468)

Variable	Coef.	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
Panel A: Main Equation					
Demographics					
Male	0.11	0.16	0.51	-0.21	0.42
Age	0.02	0.02	0.27	-0.02	0.07
Age squared	0.00	0.00	0.40	0.00	0.00
White (ethnicity)	0.53	0.39	0.18	-0.24	1.29
Indices of deprivation	-0.01	0.02	0.42	-0.05	0.02
Partner	0.13	0.10	0.18	-0.06	0.32
Presence of children	-0.11	0.14	0.43	-0.38	0.16
Employed	-0.17	0.10	0.09	-0.37	0.02
Degree level education	0.20	0.11	0.08	-0.03	0.42
Perception of local area	0.00	0.00	0.82	-0.01	0.01
Weight factors					
BMI (initial)	-0.03	0.01	0.00	-0.05	-0.01
Weight change (kg) week 2	-0.23	0.04	0.00	-0.32	-0.14
Aspect of the programme					
Self-referred	0.17	0.09	0.05	0.00	0.33
Days (referral to registration)	0.00	0.00	0.75	-0.01	0.01
Days (registration to start)	0.01	0.01	0.02	0.00	0.02
Consistent attendance	0.58	0.10	0.00	0.39	0.78
Health behaviours					
Smokes	0.20	0.16	0.21	-0.11	0.51
Excess alcohol consumption	-0.23	0.15	0.12	-0.51	0.06
Perception of diet	-0.01	0.00	0.08	-0.01	0.00
Energy expenditure (kcal/day)	0.00	0.00	0.49	0.00	0.00
Physical health					
Disabled	0.15	0.22	0.49	-0.28	0.59
Cardiovascular disease	-0.06	0.16	0.72	-0.37	0.26
Mobility problems	-0.02	0.10	0.85	-0.22	0.19
Diabetes	-0.12	0.14	0.39	-0.40	0.15
Hypertension	0.08	0.11	0.46	-0.13	0.30
Mental health					
Depression	0.11	0.16	0.50	-0.21	0.42
Stress	-0.15	0.18	0.40	-0.49	0.20
Personality					
Openness	0.00	0.00	0.76	0.00	0.00
Neuroticism	0.00	0.00	0.79	0.00	0.00
Conscientiousness	0.00	0.00	0.47	0.00	0.01
Agreeableness	0.00	0.00	0.69	0.00	0.01
Extroversion	0.00	0.00	0.11	0.00	0.01
_cons	-0.89	0.97	0.36	-2.78	1.01

Panel B: Selection Equation					
Demographics					
Male	0.12	0.16	0.46	-0.20	0.44
Age	0.02	0.02	0.23	-0.01	0.06
Age squared	0.00	0.00	0.54	0.00	0.00
White (ethnicity)	0.00	0.33	0.99	-0.66	0.65
Indices of deprivation	-0.02	0.02	0.28	-0.05	0.01
Partner	0.07	0.08	0.37	-0.09	0.24
Presence of children	-0.35	0.11	0.00	-0.57	-0.12
Employed	0.02	0.09	0.86	-0.16	0.19
Degree level education	0.05	0.10	0.63	-0.15	0.25
Perception of local area	0.00	0.00	0.32	0.00	0.01
Weight factors					
BMI (initial)	0.01	0.01	0.15	-0.01	0.03
Weight change (kg) week 2	-0.11	0.02	0.00	-0.14	-0.07
Aspect of the programme					
Self-referred	-0.04	0.08	0.63	-0.19	0.11
Days (referral to registration)	0.00	0.00	0.38	0.00	0.01
Days (registration to start)	-0.01	0.00	0.00	-0.02	0.00
Consistent attendance	0.05	0.08	0.52	-0.10	0.20
Health behaviours					
Smokes	-0.28	0.12	0.02	-0.52	-0.05
Excess alcohol consumption	0.15	0.14	0.29	-0.13	0.42
Perception of diet	0.00	0.00	0.06	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.33	0.00	0.00
Physical health					
Disabled	0.33	0.20	0.09	-0.06	0.72
Cardiovascular disease	0.10	0.16	0.54	-0.22	0.42
Mobility problems	0.12	0.10	0.22	-0.07	0.31
Diabetes	0.21	0.14	0.15	-0.07	0.49
Hypertension	-0.07	0.11	0.50	-0.28	0.14
Mental health					
Depression	-0.25	0.12	0.05	-0.49	0.00
Stress	-0.05	0.15	0.76	-0.34	0.25
Personality					
Openness	0.00	0.00	0.80	0.00	0.00
Neuroticism	0.00	0.00	0.98	0.00	0.00
Conscientiousness	0.00	0.00	0.81	0.00	0.00
Agreeableness	0.00	0.00	0.94	0.00	0.00
Extroversion	0.00	0.00	0.48	0.00	0.00
_cons	-0.67	0.65	0.30	-1.95	0.60
ρ	-0.35	0.47		-0.88	0.59

Likelihood ratio Test of ρ = 0: chi2(1) = 0.32, p-value = 0.57

Table 4.5: Percentage weight change controlling for sample selection at week 12
Result of the FIML Estimation (all variables, n=1,468)

Variable	Coef.	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
Panel A: Main Equation					
Demographics					
Male	-0.25	0.38	0.51	-0.99	0.49
Age	-0.09	0.05	0.06	-0.19	0.00
Age squared	0.00	0.00	0.16	0.00	0.00
White (ethnicity)	-2.40	0.98	0.02	-4.32	-0.47
Indices of deprivation	-0.04	0.04	0.36	-0.13	0.05
Partner	-0.14	0.22	0.52	-0.58	0.30
Presence of children	0.09	0.32	0.77	-0.53	0.72
Employed	0.15	0.24	0.54	-0.33	0.63
Degree level education	-0.72	0.27	0.01	-1.26	-0.19
Perception of local area	0.00	0.01	0.48	-0.02	0.01
Weight factors					
BMI (initial)	0.08	0.03	0.01	0.02	0.13
Weight change (kg) week 2	0.68	0.07	0.00	0.55	0.80
Aspect of the programme					
Self-referred	-0.23	0.21	0.28	-0.64	0.18
Days (referral to registration)	-0.01	0.01	0.55	-0.02	0.01
Days (registration to start)	-0.03	0.01	0.04	-0.06	0.00
Consistent attendance	-1.86	0.28	0.00	-2.41	-1.32
Health behaviours					
Smokes	-0.76	0.39	0.05	-1.53	0.00
Excess alcohol consumption	0.44	0.38	0.24	-0.30	1.18
Perception of diet	0.01	0.01	0.10	0.00	0.03
Energy expenditure (kcal/day)	0.00	0.00	0.71	0.00	0.00
Physical health					
Disabled	-0.30	0.49	0.55	-1.26	0.66
Cardiovascular disease	0.26	0.39	0.50	-0.51	1.03
Mobility problems	0.15	0.25	0.56	-0.34	0.64
Diabetes	0.76	0.35	0.03	0.08	1.45
Hypertension	-0.25	0.27	0.36	-0.78	0.28
Mental health					
Depression	0.25	0.38	0.51	-0.50	1.00
Stress	0.03	0.43	0.95	-0.82	0.88
Personality					
Openness	0.00	0.00	0.88	-0.01	0.01
Neuroticism	0.00	0.00	0.46	-0.01	0.01
Conscientiousness	0.00	0.01	0.72	-0.01	0.01
Agreeableness	0.00	0.01	0.83	-0.01	0.01
Extroversion	-0.01	0.00	0.06	-0.02	0.00
_cons	-0.61	2.31	0.79	-5.13	3.90

Panel B: Selection Equation					
Demographics					
Male	0.17	0.14	0.23	-0.11	0.45
Age	0.01	0.02	0.47	-0.02	0.04
Age squared	0.00	0.00	1.00	0.00	0.00
White (ethnicity)	0.06	0.31	0.86	-0.55	0.67
Indices of deprivation	-0.01	0.01	0.49	-0.04	0.02
Partner	-0.03	0.08	0.67	-0.18	0.12
Presence of children	-0.25	0.10	0.01	-0.45	-0.06
Employed	0.01	0.08	0.88	-0.15	0.17
Degree level education	0.01	0.09	0.87	-0.17	0.20
Perception of local area	0.00	0.00	0.69	-0.01	0.00
Weight factors					
BMI (initial)	0.03	0.01	0.01	0.01	0.04
Weight change (kg) week 2	-0.09	0.02	0.00	-0.12	-0.06
Aspect of the programme					
Self-referred	0.06	0.07	0.41	-0.08	0.20
Days (referral to registration)	0.00	0.00	0.73	-0.01	0.01
Days (registration to start)	-0.01	0.00	0.01	-0.02	0.00
Consistent attendance	0.32	0.07	0.00	0.19	0.46
Health behaviours					
Smokes	-0.21	0.12	0.07	-0.44	0.02
Excess alcohol consumption	-0.05	0.12	0.68	-0.29	0.19
Perception of diet	0.00	0.00	0.35	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.09	0.00	0.00
Physical health					
Disabled	0.09	0.17	0.61	-0.25	0.43
Cardiovascular disease	0.21	0.15	0.15	-0.07	0.50
Mobility problems	0.07	0.09	0.42	-0.10	0.24
Diabetes	0.25	0.13	0.05	0.00	0.50
Hypertension	-0.11	0.10	0.23	-0.30	0.07
Mental health					
Depression	-0.17	0.12	0.15	-0.40	0.06
Stress	-0.07	0.14	0.63	-0.35	0.21
Personality					
Openness	0.00	0.00	0.12	-0.01	0.00
Neuroticism	0.00	0.00	0.66	0.00	0.00
Conscientiousness	0.00	0.00	0.82	0.00	0.00
Agreeableness	0.00	0.00	0.84	0.00	0.00
Extroversion	0.00	0.00	0.96	0.00	0.00
_cons	-0.94	0.61	0.12	-2.13	0.25
ρ	0.23	0.35		-0.46	0.74

Likelihood ratio Test of ρ = 0: chi2(1) = 0.20, p-value = 0.65

Table 4.6: BMI change controlling for sample selection at week 12
Result of the FIML Estimation (all variables, n=1,468)

Variable	Coef.	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
		Panel A: Main Equation			
		Demographics			
Male	-0.18	0.15	0.22	-0.48	0.11
Age	-0.04	0.02	0.04	-0.08	0.00
Age squared	0.00	0.00	0.27	0.00	0.00
White (ethnicity)	-0.85	0.38	0.03	-1.60	-0.10
Indices of deprivation	-0.01	0.02	0.66	-0.04	0.03
Partner	-0.04	0.09	0.61	-0.22	0.13
Presence of children	0.24	0.12	0.04	0.01	0.47
Employed	0.04	0.10	0.70	-0.15	0.23
Degree level education	-0.25	0.11	0.02	-0.46	-0.04
Perception of local area	0.00	0.00	0.72	-0.01	0.00
		Weight factors			
BMI (initial)	-0.05	0.01	0.00	-0.07	-0.03
Weight change (kg) week 2	0.31	0.02	0.00	0.27	0.35
		Aspect of the programme			
Self-referred	-0.10	0.08	0.21	-0.26	0.06
Days (referral to registration)	0.00	0.00	0.36	-0.01	0.00
Days (registration to start)	0.00	0.00	0.51	-0.01	0.01
Consistent attendance	-0.91	0.08	0.00	-1.07	-0.74
		Health behaviours			
Smokes	-0.09	0.15	0.52	-0.38	0.19
Excess alcohol consumption	0.20	0.15	0.17	-0.09	0.49
Perception of diet	0.00	0.00	0.50	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.10	0.00	0.00
		Physical health			
Disabled	-0.22	0.19	0.25	-0.60	0.16
Cardiovascular disease	-0.01	0.15	0.93	-0.32	0.29
Mobility problems	0.03	0.10	0.78	-0.17	0.22
Diabetes	0.14	0.13	0.28	-0.12	0.40
Hypertension	-0.02	0.11	0.88	-0.22	0.19
		Mental health			
Depression	0.23	0.15	0.11	-0.05	0.52
Stress	0.07	0.17	0.70	-0.27	0.40
		Personality			
Openness	0.00	0.00	0.53	0.00	0.00
Neuroticism	0.00	0.00	0.39	-0.01	0.00
Conscientiousness	0.00	0.00	0.85	0.00	0.01
Agreeableness	0.00	0.00	0.96	0.00	0.00
Extroversion	0.00	0.00	0.14	-0.01	0.00
_cons	3.55	0.73	0.00	2.13	4.98

Panel B: Selection Equation					
Demographics					
Male	0.23	0.14	0.09	-0.04	0.50
Age	0.01	0.02	0.58	-0.02	0.04
Age squared	0.00	0.00	0.86	0.00	0.00
White (ethnicity)	0.14	0.31	0.64	-0.46	0.74
Indices of deprivation	-0.01	0.01	0.56	-0.04	0.02
Partner	-0.03	0.08	0.70	-0.18	0.12
Presence of children	-0.28	0.10	0.01	-0.47	-0.08
Employed	0.03	0.08	0.69	-0.12	0.19
Degree level education	0.03	0.09	0.73	-0.15	0.21
Perception of local area	0.00	0.00	0.67	-0.01	0.00
Weight factors					
BMI (initial)	0.03	0.01	0.00	0.01	0.05
Weight change (kg) week 2	-0.09	0.02	0.00	-0.12	-0.06
Aspect of the programme					
Self-referred	0.04	0.07	0.55	-0.09	0.18
Days (referral to registration)	0.00	0.00	0.71	0.00	0.01
Days (registration to start)	-0.01	0.00	0.00	-0.02	0.00
Consistent attendance	0.33	0.07	0.00	0.19	0.46
Health behaviours					
Smokes	-0.19	0.12	0.11	-0.41	0.04
Excess alcohol consumption	-0.07	0.12	0.56	-0.31	0.17
Perception of diet	0.00	0.00	0.59	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.07	0.00	0.00
Physical health					
Disabled	0.10	0.17	0.58	-0.24	0.43
Cardiovascular disease	0.17	0.14	0.23	-0.11	0.45
Mobility problems	0.05	0.09	0.53	-0.12	0.22
Diabetes	0.25	0.12	0.04	0.01	0.49
Hypertension	-0.14	0.09	0.14	-0.32	0.04
Mental health					
Depression	-0.15	0.12	0.20	-0.38	0.08
Stress	-0.04	0.14	0.78	-0.31	0.23
Personality					
Openness	0.00	0.00	0.09	-0.01	0.00
Neuroticism	0.00	0.00	0.40	0.00	0.00
Conscientiousness	0.00	0.00	0.92	0.00	0.00
Agreeableness	0.00	0.00	0.56	-0.01	0.00
Extroversion	0.00	0.00	0.81	0.00	0.00
_cons	-1.03	0.60	0.09	-2.20	0.14
ρ	-0.78	0.06		-0.88	-0.63

Likelihood ratio Test of ρ = 0: chi2(1) = 10.28 , p-value = <0.01

Table 4.7: Significant weight loss controlling for sample selection at week 12
Result of the FIML Estimation (all variables, n=1,468)

Variable	Coef.	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
Panel A: Main Equation					
Demographics					
Male	0.07	0.16	0.65	-0.23	0.38
Age	0.03	0.02	0.09	0.00	0.07
Age squared	0.00	0.00	0.35	0.00	0.00
White (ethnicity)	0.54	0.39	0.17	-0.22	1.31
Indices of deprivation	-0.02	0.02	0.30	-0.05	0.02
Partner	0.04	0.09	0.68	-0.14	0.21
Presence of children	-0.39	0.12	0.00	-0.63	-0.15
Employed	-0.05	0.10	0.59	-0.25	0.14
Degree level education	0.17	0.11	0.14	-0.05	0.39
Perception of local area	0.00	0.00	0.96	-0.01	0.01
Weight factors					
BMI (initial)	-0.01	0.01	0.66	-0.03	0.02
Weight change (kg) week 2	-0.23	0.04	0.00	-0.30	-0.16
Aspect of the programme					
Self-referred	0.07	0.08	0.37	-0.09	0.23
Days (referral to registration)	0.00	0.00	0.79	-0.01	0.01
Days (registration to start)	0.01	0.01	0.44	-0.01	0.02
Consistent attendance	0.71	0.11	0.00	0.48	0.93
Health behaviours					
Smokes	-0.02	0.15	0.90	-0.32	0.28
Excess alcohol consumption	-0.18	0.15	0.23	-0.46	0.11
Perception of diet	0.00	0.00	0.76	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.08	0.00	0.00
Physical health					
Disabled	0.14	0.20	0.50	-0.26	0.54
Cardiovascular disease	0.10	0.16	0.53	-0.21	0.41
Mobility problems	0.11	0.10	0.26	-0.08	0.31
Diabetes	-0.19	0.15	0.21	-0.49	0.11
Hypertension	0.03	0.12	0.78	-0.19	0.26
Mental health					
Depression	-0.04	0.15	0.78	-0.33	0.25
Stress	-0.26	0.18	0.13	-0.61	0.08
Personality					
Openness	0.00	0.00	0.18	-0.01	0.00
Neuroticism	0.00	0.00	0.64	0.00	0.00
Conscientiousness	0.00	0.00	0.47	-0.01	0.00
Agreeableness	0.00	0.00	0.87	0.00	0.00
Extroversion	0.00	0.00	0.54	0.00	0.01
_cons	-1.97	0.71	0.01	-3.36	-0.59

Panel B: Selection Equation					
Demographics					
Male	0.17	0.14	0.22	-0.10	0.44
Age	0.01	0.02	0.52	-0.02	0.04
Age squared	0.00	0.00	0.93	0.00	0.00
White (ethnicity)	0.12	0.31	0.70	-0.49	0.73
Indices of deprivation	-0.01	0.01	0.62	-0.04	0.02
Partner	-0.03	0.08	0.65	-0.18	0.12
Presence of children	-0.25	0.10	0.01	-0.44	-0.05
Employed	0.01	0.08	0.93	-0.15	0.17
Degree level education	0.01	0.09	0.90	-0.17	0.19
Perception of local area	0.00	0.00	0.64	-0.01	0.00
Weight factors					
BMI (initial)	0.03	0.01	0.01	0.01	0.04
Weight change (kg) week 2	-0.09	0.02	0.00	-0.12	-0.06
Aspect of the programme					
Self-referred	0.05	0.07	0.44	-0.08	0.19
Days (referral to registration)	0.00	0.00	0.64	0.00	0.01
Days (registration to start)	-0.01	0.00	0.00	-0.02	0.00
Consistent attendance	0.33	0.07	0.00	0.19	0.46
Health behaviours					
Smokes	-0.21	0.12	0.07	-0.44	0.02
Excess alcohol consumption	-0.05	0.12	0.67	-0.29	0.19
Perception of diet	0.00	0.00	0.40	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.09	0.00	0.00
Physical health					
Disabled	0.09	0.17	0.62	-0.26	0.43
Cardiovascular disease	0.20	0.15	0.17	-0.08	0.49
Mobility problems	0.07	0.09	0.40	-0.10	0.25
Diabetes	0.27	0.13	0.03	0.03	0.52
Hypertension	-0.12	0.10	0.21	-0.31	0.07
Mental health					
Depression	-0.17	0.12	0.15	-0.40	0.06
Stress	-0.08	0.14	0.58	-0.35	0.20
Personality					
Openness	0.00	0.00	0.12	-0.01	0.00
Neuroticism	0.00	0.00	0.57	0.00	0.00
Conscientiousness	0.00	0.00	0.80	0.00	0.00
Agreeableness	0.00	0.00	0.88	0.00	0.00
Extroversion	0.00	0.00	0.90	0.00	0.00
_cons	-0.98	0.60	0.10	-2.16	0.19
ρ	0.88	0.17		-0.08	0.99

Likelihood ratio Test of ρ = 0: chi2(1) = 1.14 p-value = 0.29

4.8: Discussion

4.8.1: Checks for evidence of collinearity

Before discussing the results, we present evidence regarding the issue of potential multicollinearity. Following the estimation of each of the six models presented above, as per Wooldridge (2009, p617), we calculate the inverse mills ratio (λ) and estimate a regression with λ as the dependant variable on our vector of explanatory variables (*X*). We obtain R^2 values (the proportion of variability in a data set that is accounted for by a statistical model) ranging from 0.93 to 0.98. This is unsurprising given the methodology by which λ is calculated and the lack of exclusionary criteria within our model; both these concepts are discussed previously. It does, however, point towards issues of multicollinearity which warrants further discussion.

In the current context, key issues resulting from multicollinearity include; (1) large changes in the estimated coefficients and inflated standard errors when λ is added as a regressor and (2) insignificant coefficients for the explanatory variables in the regression, but a rejection of the joint hypothesis that coefficients are all zero (using an *F*-test). To explore further the potential issue of multicollinearity we regress each of the weight outcome variables of interest (Y_1) on the vector of explanatory variables (*X*) with the addition of λ as a regressor. The results of these six models are presented in Appendix 16. We can, thus, compare the estimated coefficients and standard errors for the individual explanatory variables, the F-statistics and R^2 in models including λ (Appendix 16) and excluding λ (results presented in Chapter 2) to see if we observe evidence of multicollinearity, as outlined above.

For clarity of discussions, below we present the results of the sample selection models (Tables 4.2 – 4.7) individually, followed by a brief discussion of evidence of multicollinearity for each.

4.8.2: Evidence of non-random attrition

The results in Tables 4.2 – 4.7 present the outcomes of the two equations (panel A and B), the correlation of the residuals in the two equations (ρ) and the likelihood ratio test of $\rho = 0$. If ρ is found to be significantly different from 0, this indicates correlation between the error terms of the two equations and the presence of endogenous sample selection bias.

Percentage weight loss at week ten

From Table 4.2 we find no evidence of sample selection bias; ρ=0.16 (p-value=0.59). Regarding multicollinearity, when comparing the regression including λ (Appendix 16, Table A) to the regression excluding λ (Chapter 2, Table 2.10) we observe no evidence of substantial changes in the coefficients or inflated standard errors and, therefore, the same coefficients remain significant in both models. Further, we observe little difference between the F-statistics from the two models. When including λ; F(33, 1,066)=18.16 (p-value=<0.01). When excluding λ; F(32, 1,067)=18.63 (p-value=<0.01). As a result we do not observe a difference in the R^2 values of the two models, where we find both explain 36% of variability in the datasets that is accounted for by the statistical models. In summary, we find a lack of evidence of an issue of multicollinearity.

Percentage weight loss at week twelve

From Table 4.5 we find no evidence of sample selection bias; ρ=0.23 (p-value=0.65). Regarding multicollinearity, when comparing the regression including λ (Appendix 16, Table D) and the regression excluding λ (Chapter 2, Table 2.13) we do observe some variables become insignificant, however, there is little evidence of this resulting from inflated standard errors and or substantial changes to the estimated coefficients. As presented above, we observe little difference between the F-statistics from the two models. When including λ; F(33, 818)=13.61 (p-value=<0.01). When excluding λ; F(32, 819)=14.03 (p-value=<0.01). As a result we do not observe a difference in the R^2 values of the two models, where we find both explain 35% of variability in the datasets that is accounted for by the statistical models. In summary, we again find a lack of evidence of issues of multicollinearity.

Significant weight loss at week ten

From Table 4.4 we find no evidence of sample selection bias; ρ=-0.36 (p-value=0.57). Regarding multicollinearity, we follow the methodology outlined above and again, when comparing the regression including λ (Appendix 16, Table C) to the regression excluding λ (Chapter 2, Table 2.12), we observe no evidence of substantial changes in the coefficients or inflated standard errors and, therefore, the same coefficients remain significant in both models. In contrast to analyses of percentage weight change, we use a probit model to estimate the binary variable 'significant weight loss'. This model uses maximum likelihood, an iterative process, which maximises the joint likelihood of the observed values of the dependent variable given the values of the explanatory variables and the estimated parameters. The output of this model includes a listing of the log likelihoods at each iteration. The first iteration is the log likelihood of the "null" model i.e. the model containing no predictors. In the next iteration, the predictors are included in the model. With each iteration, the log likelihood increases until the model converges i.e. when the difference between the iterations is very small. The log likelihood of the final model has no meaning in itself; however, we can use the likelihood ratio (LR) chi-squared test, to compare our two regression models (Long, 2006). We observe little difference between the LR chi-squared tests from the two models. When including λ; χ^2 (33)=266.32 (p-value=<0.01). When excluding λ; χ^2 (32)=264.87 (p-value=<0.01). The probit model does not, however, have an equivalent R^2. In summary, and based on our observations, we find a lack of evidence of issues of multicollinearity.

Significant weight loss at week twelve

Reflecting findings above, from Table 4.7 we find no evidence of sample selection bias, *ρ*=0.88 (p-value=0.29). Similarly, regarding multicollinearity, when comparing the regression including λ (Appendix 16, Table F) to the regression excluding λ (Chapter 2, Table 2.15) we observe no evidence of substantial changes in the coefficients or inflated standard errors and, therefore, the same coefficients remain significant in both models. Further, we observe little difference between the LR chi-squared tests from the two models. When including λ; χ^2 (33)=225.71 (p-value=<0.01). When excluding λ; χ^2 (32)=225.51 (p-value=<0.01). Again, we find a lack of evidence of issues of multicollinearity.

BMI change at week ten

In Table 4.3 we do, however, find evidence of sample selection bias; *ρ*=0.88 (p-value=0.29). We discuss the implications of this finding later. With regards to multicollinearity, when comparing the regression including λ (Appendix 16, Table B) and the regression excluding λ

(Chapter 2, Table 2.11) we do observe some variable become insignificant, however, there is little evidence of this resulting from inflated standard errors and or substantial changes to the estimated coefficients. Further, we observe little difference between the F-statistics from the two models. When including λ; $F(33, 1{,}066)=8.74$ (p-value=<0.01). When excluding λ; $F(32, 1{,}067)=9.02$ (p-value=<0.01). As a result we do not observe a difference in the R^2 values of the two models, where we find both explain 21% of variability in the data sets that is accounted for by the statistical models. In summary, we find a lack of evidence of issues of multicollinearity.

BMI change at week twelve

Both sample selection and multicollinearity findings above are reflected in analyses of BMI change at week 12. From Table 4.6 we find evidence of sample selection bias; ρ=-0.78 (p-value=<0.01) and, regarding multicollinearity, we observe one variable become insignificant (see Appendix 16, Table E and Chapter 2, Table 2.14), however, there is little evidence of this resulting from inflated standard errors and or substantial changes to the estimated coefficients. We observe little difference between the F-statistics from the two models. When including λ; $F(33, 818)= 16.56$ (p-value=<0.01). When excluding λ; $F(32, 819)= 17.07$ (p-value=<0.01). As a result we do not observe a difference in the R^2 values of the two models, where we find both explain 40% of variability in the data sets that is accounted for by the statistical models. We, therefore, find a lack of evidence of issues of multicollinearity across all six sample selection models presented.

In the analyses of BMI, evidence of sample selection suggests an unobserved variable(s) is significant to both engagement at weeks ten and twelve and BMI change and weeks ten and twelve, thus, attrition is non-random and results of the previous OLS regressions are biased. The method applied in this chapter uses information from all individuals who started the weight management service to improve the estimates of the parameters in the regression model. Whilst the results suggest that sample selection bias is present, further tests are required to identify the effect controlling for sample selection has had on the coefficients of the explanatory variables and the constant.

4.8.3: BMI change at week 10

Table 4.8 presents the coefficients and standard errors obtained using OLS and FIML analyses of BMI change at week 10. Following each procedure (OLS and FIML) the estimates were stored and t-tests were conducted to identify significant differences in the estimated coefficients from the OLS and FIML models. The p-values of these tests are presented in the final column of the tables. From the table we observe the coefficients of three of the explanatory variables ('*Presence of children', 'Weight change (kg) at week 2'* and '*Smokes*') and the constant term estimated from the OLS model differ significantly from those estimated using the FIML model.

4.8.4: BMI change at week 12

Table 4.9 presents the coefficients and standard errors obtained using OLS and FIML analyses of BMI change at week 12. Following each procedure (OLS and FIML) the estimates were stored and t-tests were conducted to identify significant differences in the estimated coefficients from the OLS and FIML models. The p-values of these tests are presented in the final column of the tables. From the table we observe the coefficients of five of the explanatory variables ('*Presence of children' 'BMI (initial)', 'Weight change (kg) week 2',* *'Days (registration to start)' and 'Consistent attendance'*) and the constant term estimated from the OLS model differ significantly from those estimated using the FIML model. These findings are further discussed below.

Table 4.8: Determinants of BMI change at week 10: Comparing the results of FIML selection model and OLS

Variable	OLS Coefficient	OLS SE	FIML Coefficient	FIML SE	p-value
	Demographics				
Male	-0.24	0.17	-0.22	0.18	0.80
Age	-0.01	0.02	0.00	0.02	0.20
Age squared	0.00	0.00	0.00	0.00	0.44
White (ethnicity)	-0.57	0.42	-0.59	0.45	0.93
Indices of deprivation	-0.01	0.02	-0.02	0.02	0.32
Partner	-0.05	0.10	0.01	0.11	0.29
Presence of children	0.12	0.12	-0.08	0.14	0.02
Employed	0.04	0.11	0.07	0.11	0.63
Degree level education	-0.12	0.12	-0.10	0.13	0.75
Perception of local area	0.00	0.00	0.00	0.00	0.39
	Weight factors				
BMI (initial)	-0.04	0.01	-0.03	0.01	0.22
Weight change (kg) week 2	0.23	0.02	0.16	0.02	0.00
	Aspect of the programme				
Self-referred	-0.15	0.09	-0.17	0.10	0.73
Days (referral to registration)	0.00	0.00	0.00	0.00	0.29
Days (registration to start)	-0.01	0.01	-0.02	0.01	0.06
Consistent attendance	-0.62	0.09	-0.57	0.10	0.37
	Health behaviours				
Smokes	-0.40	0.16	-0.62	0.17	0.05
Excess alcohol consumption	0.23	0.16	0.32	0.17	0.29
Perception of diet	0.00	0.00	0.01	0.00	0.09
Energy expenditure	0.00	0.00	0.00	0.00	0.49
	Physical health				
Disabled	-0.25	0.21	-0.05	0.23	0.09
Cardiovascular disease	0.44	0.17	0.48	0.19	0.68
Mobility problems	0.02	0.11	0.12	0.12	0.15
Diabetes	-0.03	0.15	0.10	0.16	0.14
Hypertension	0.04	0.12	-0.02	0.13	0.36
	Mental health				
Depression	0.17	0.16	0.03	0.17	0.14
Stress	-0.12	0.18	-0.19	0.20	0.52
	Personality				
Openness	0.00	0.00	0.00	0.00	0.99
Neuroticism	0.00	0.00	0.00	0.00	0.56
Conscientiousness	0.00	0.00	0.00	0.00	0.77
Agreeableness	0.00	0.00	0.00	0.00	0.61
Extroversion	0.00	0.00	0.00	0.00	0.61
_cons	1.14	0.79	-0.44	0.86	0.01

Table 4.9: Determinants of BMI change at week 12: Comparing the results of FIML selection model and OLS

Variable	OLS Coefficient	OLS SE	FIML Coefficient	FIML SE	p-value
Demographics					
Male	-0.12	0.13	-0.18	0.15	0.41
Age	-0.03	0.02	-0.04	0.02	0.27
Age squared	0.00	0.00	0.00	0.00	0.72
White (ethnicity)	-0.86	0.35	-0.85	0.38	0.95
Indices of deprivation	-0.01	0.02	-0.01	0.02	0.39
Partner	-0.06	0.08	-0.04	0.09	0.71
Presence of children	0.11	0.10	0.24	0.12	0.02
Employed	0.04	0.09	0.04	0.10	0.99
Degree level education	-0.24	0.10	-0.25	0.11	0.93
Perception of local area	0.00	0.00	0.00	0.00	0.75
Weight factors					
BMI (initial)	-0.04	0.01	-0.05	0.01	0.03
Weight change (kg) week 2	0.27	0.02	0.31	0.02	0.00
Aspect of the programme					
Self-referred	-0.06	0.07	-0.10	0.08	0.30
Days (referral to registration)	0.00	0.00	0.00	0.00	0.73
Days (registration to start)	-0.01	0.00	0.00	0.00	0.03
Consistent attendance	-0.73	0.07	-0.91	0.08	0.00
Health behaviours					
Smokes	-0.23	0.13	-0.09	0.15	0.06
Excess alcohol consumption	0.17	0.13	0.20	0.15	0.65
Perception of diet	0.00	0.00	0.00	0.00	0.21
Energy expenditure	0.00	0.00	0.00	0.00	0.15
Physical health					
Disabled	-0.17	0.17	-0.22	0.19	0.57
Cardiovascular disease	0.10	0.14	-0.01	0.15	0.11
Mobility problems	0.07	0.09	0.03	0.10	0.34
Diabetes	0.26	0.12	0.14	0.13	0.07
Hypertension	-0.07	0.09	-0.02	0.11	0.34
Mental health					
Depression	0.14	0.13	0.23	0.15	0.19
Stress	0.01	0.15	0.07	0.17	0.49
Personality					
Openness	0.00	0.00	0.00	0.00	0.19
Neuroticism	0.00	0.00	0.00	0.00	0.81
Conscientiousness	0.00	0.00	0.00	0.00	0.73
Agreeableness	0.00	0.00	0.00	0.00	0.97
Extroversion	0.00	0.00	0.00	0.00	0.88
_cons	2.26	0.65	3.55	0.73	0.00

4.8.5: Changes to the constant

In analyses of BMI change the most significant differences between the OLS and FIML estimates is seen in the constant terms suggesting a general shift in estimated outcomes, with relatively small impacts on the estimated coefficients of the explanatory variables when controlling for selection bias.

BMI change at week 10

In analyses of BMI change at week 10, the OLS estimate of the constant is 1.14, compared to a significantly lower FIML estimation of -0.44 (p-value=0.01). The significant difference observed in the constant implies an overall downward shift in estimated outcomes, i.e. the reduction in BMI is greater when controlling for sample selection. To contextualise this change in the constant term, Table 4.10 presents the fitted and predicted values of BMI change when using OLS and FIML models. The expected value of the BMI change at week 10 from the underlying distribution of the OLS regression model is -1.90 compared to an expected value from the FIML model of -2.49.

	Obs	**Mean**	**SD**	**Min**	**Max**
OLS	1468	-1.90	0.72	-5.42	0.52
FIML	1468	-2.49	0.65	-4.98	-0.41

Table 4.10: Comparison of expected values of BMI change at week 10

Figure 4.2 presents the Kernel density distributions of the expected values from both models. It evidences a clear leftward shift in the distribution curve from OLS estimates to those predicted by the FIML model indicting a greater expected BMI reduction when controlling for sample selection.

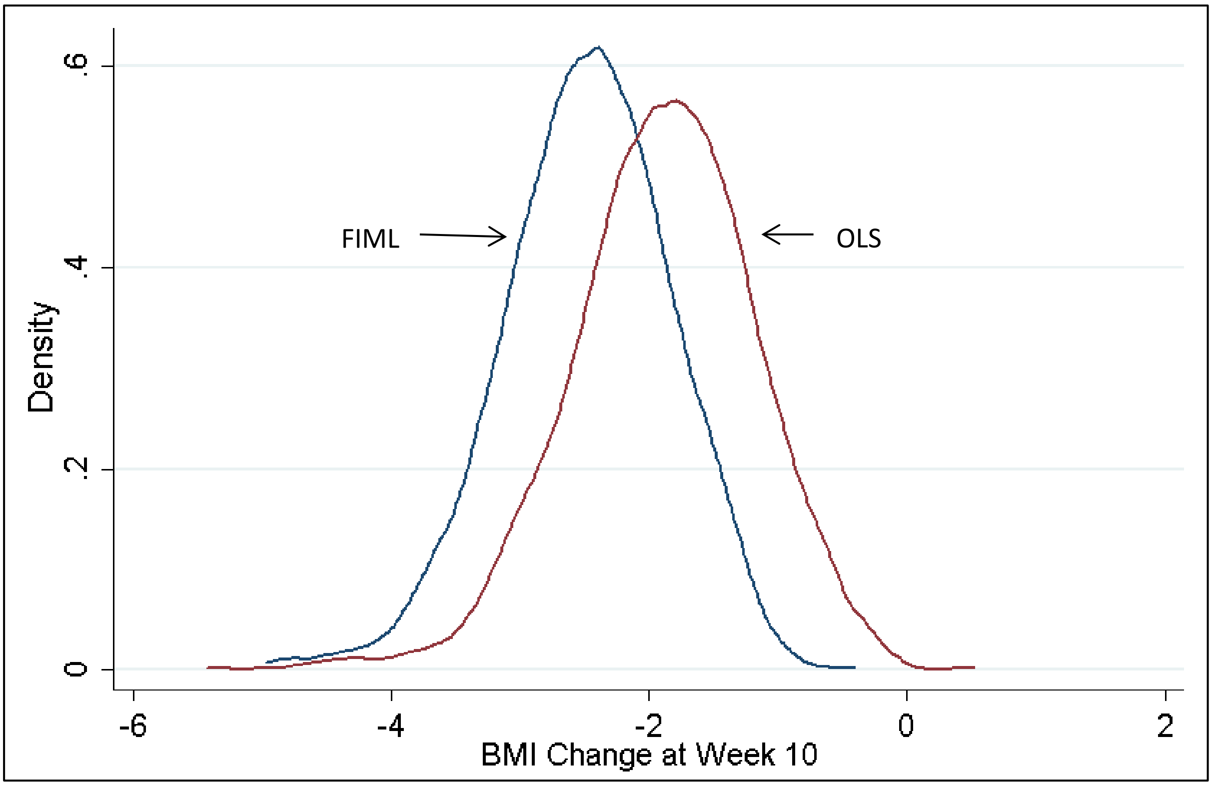


Figure 4.2: Kernel density estimates- BMI change at week 10 (OLS and FIML models)

BMI change at week 12

In contrast, in analyses of BMI change at week 12, the OLS estimate of the constant is 2.26, compared to a significantly higher FIML estimation of 3.55 (p-value=<0.01). The significant difference observed in the constant implies an overall upward shift in estimated outcomes, i.e. the reduction in BMI is smaller when controlling for sample selection. To contextualise this change in the constant term, Table 4.11 presents the fitted and predicted values of BMI change when using OLS and FIML models. The expected value of the BMI change at week 12 from the underlying distribution of the OLS regression model is -2.23 compared to an expected value from the FIML model of -1.57.

	Obs	Mean	SD	Min	Max
OLS	1468	-2.23	0.81	-6.20	0.82
FIML	1468	-1.57	0.96	-6.37	1.72

Table 4.11: Comparison of expected values of BMI change at week 12

Figure 4.3 presents the Kernel density distributions of the expected values from both models. It evidences a clear rightward shift in the distribution curve from OLS estimates to those predicted by the FIML model indicting a more modest expected BMI change when controlling for sample selection.

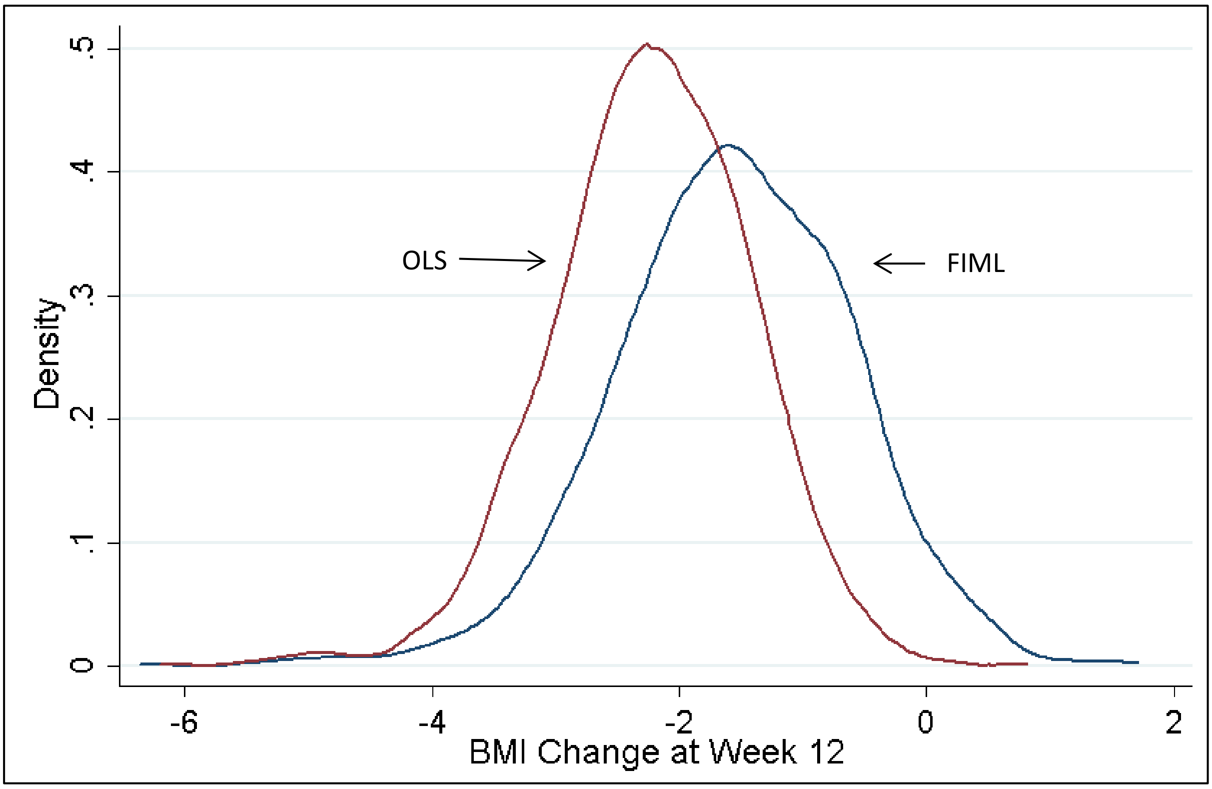


Figure 4.3: Kernel density estimates- BMI change at week 12 (OLS and FIML models)

We can also compare our estimates from FIML methods to observed outcomes derived from the two imputation methods popular in the literature; (1) LOCF and (2) BOCF.

BMI change at week 10

Table 4.12 presents the estimated BMI change at week 10 using the LOCF method, the BOCF method and our expected values from the FIML and OLS models. The estimated value of BMI change at week 12 from the LOCF method is -1.68 and the estimated value from the BOCF method is -1.36.

	Obs	Mean	SD	Min	Max
OLS	1468	-1.90	0.72	-5.42	0.52
FIML	1468	-2.49	0.65	-4.98	-0.41
LOCF	1468	-1.68	0.72	-5.64	0.82
BOCF	1468	-1.36	0.73	-5.07	1.07

Table 4.12: Comparison of expected and imputed BMI change at week 10

Figure 4.4 presents the Kernel density distributions of the expected values from the models. From this Figure we can see that the FIML model produces distinctly different estimates compared to the three other approaches.

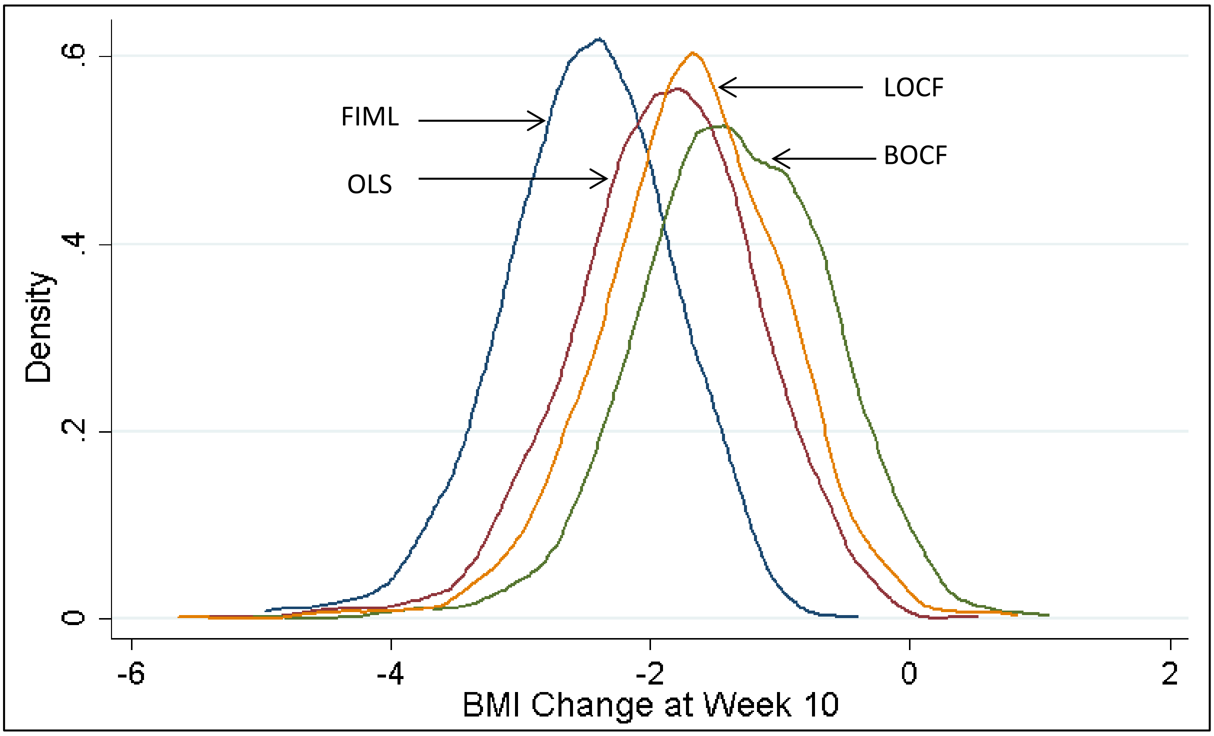


Figure 4.4: Kernel density estimates- BMI change at week 10 (OLS, FIML, BOCF and LOCF)

BMI change at week 12

Table 4.13 presents the estimated BMI change at week 12 using the LOCF method, the BOCF method and our expected values from the FIML and OLS models. The estimated value of BMI change at week 12 from the LOCF method is -1.83 and the estimated value from the BOCF method is -1.37. As expected, when using the LOCF method we suffer from exaggerated expected outcomes (although lesser than using OLS methods) and when using the BOCF method we suffer from overly conservative estimates.

	Obs	Mean	SD	Min	Max
OLS	1468	-2.23	0.81	-6.20	0.82
FIML	1468	-1.57	0.96	-6.37	1.72
LOCF	1468	-1.83	0.79	-6.04	0.96
BOCF	1468	-1.37	0.76	-5.15	0.89

Table 4.13: Comparison of expected and imputed BMI change at week 12

Figure 4.5 presents the Kernel density distributions of the expected values from the models. From this Figure we can see that LOCF and BOCF methods perhaps provide a better estimates compared to exclusionary OLS methods, however, they still suffer from over- and under-representation of outcomes respectively.

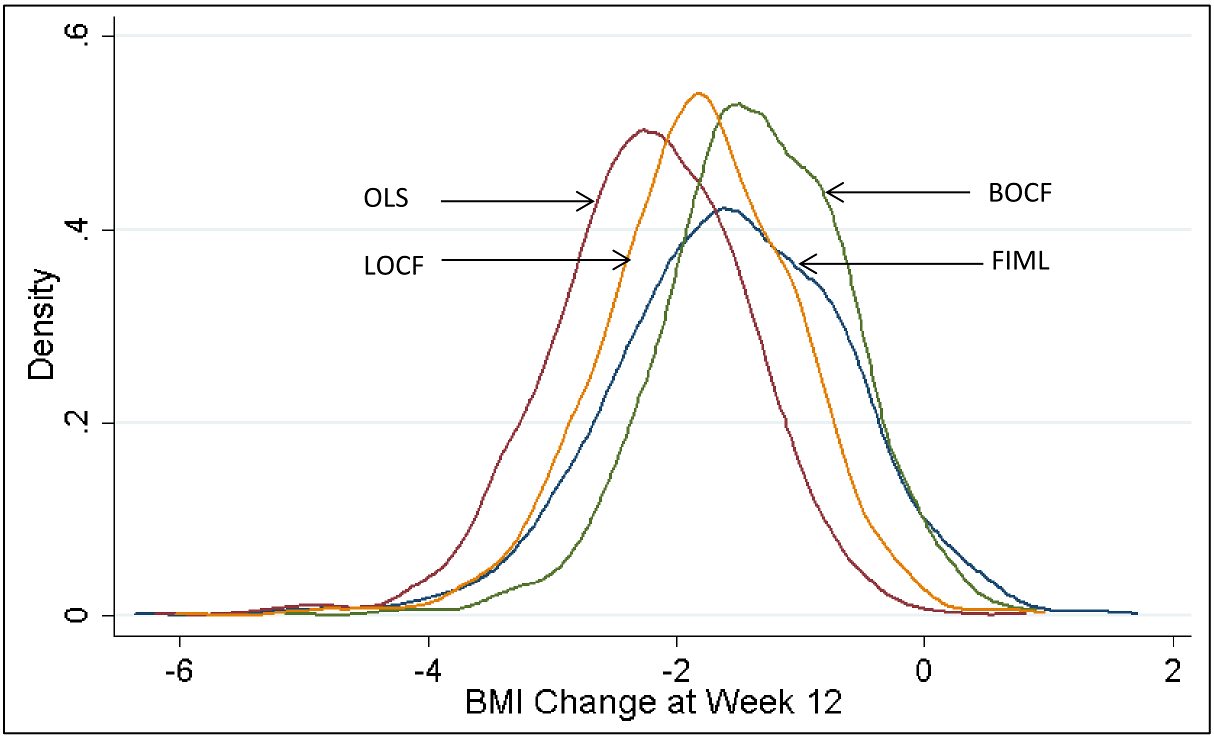


Figure 4.5: Kernel density estimates- BMI change at week 12 (OLS, FIML, BOCF and LOCF)

This section has presented evidence for a significant shift in the constant term when controlling for sample selection. Further, we contextualise this effect by presenting estimated BMI change from the various approaches outlined previously in this Chapter. The significant change in the constant term in week ten analyses, represents an overall downward shift in BMI change in the FIML model which controls for sample selection (presented in this chapter) compared to the OLS model which does not control for sample selection (presented in Chapter 2). This downward shift reflects a significantly greater expected reduction in BMI as a result of the weight management service when controlling for individuals who started the service but did not attend week ten. The significant change in the constant term in week twelve analyses, represents an overall upward shift in BMI change in the FIML model which controls for sample selection (presented in this chapter) compared to the OLS model which does not control for sample selection (presented in Chapter 2). This upward shift reflects a significantly lesser expected reduction in BMI as a result of the weight management service when controlling for individuals who started the service but did not attend week twelve. The importance of this finding is evidence of a requirement to correct for non-random attrition in analysis of BMI change as estimates from non-corrected methods may be biased. In practice, our findings have particular implications in cost-benefit analyses and research concerning return-on-investment. These activities rely on accurate estimates of expected outcomes of interventions to calculate a comparable efficacy of investment. Our research has shown that relying on expected outcomes from simple regression techniques may lead to sub-optimal estimated outcomes and, thus, sub-optimal decisions regarding which interventions and strategies to pursue. To demonstrate, the difference between the FIML and OLS estimates of BMI change at week twelve is 0.7 (Table 4.13). Jolly et al. (2011) present the resulting BMI change from six weight management services without controlling for sample selection[46]. The difference in BMI change between the best and second best performing service is 0.4. Evidently, had the study controlled for sample selection, both the estimated outcomes and recommendations for the commissioning of such services may have been significantly different.

[46] Weight Watchers, Slimming World, Rosemary Conley, Size Down and General Practice.

4.7.6: Changes in the marginal effects

The coefficients of several variables[47] vary significantly when analysed using OLS compared to FIML approaches, as presented in Tables 4.8 and 4.9. Whilst significant, we observed largely minor differences in the coefficients resulting in largely no alternations to previous conclusions regarding the associations between the variables and BMI change.

Consistent Attendance

Whilst our conclusions regarding the relationship between consistent attendance and BMI change at week 12 are not altered, we do observe a relatively large difference between the OLS and FIML coefficients. In both analyses consistent attendance is associated with a greater reduction in BMI at week 12, however, the OLS analysis estimates the effect of consistent attendance to be -0.74 whereas the FIML analysis estimate this effect at -0.93 (p-value=<0.01).

[47] In the analysis of week 10 we observe significant differences in the coefficients of 'presence of children', 'initial BMI', 'initial weight change' and 'smokes'. In the analysis of week 12 we observe significant differences in the coefficients of 'presence of children', 'initial BMI', 'initial weight change', 'days between registering and starting the service' and 'consistent attendance'.

4.9: Conclusion

The coefficients of some variables are significantly different in analyses utilising FIML models compared to OLS models, however, they do not change the conclusions of the previous chapters. When controlling for sample selection using the FIML model we do, however, observe a significant change in the constant term observing a significantly greater reduction in BMI at week 10 and significantly smaller reduction in BMI at week 12.

Chapter 5

BMI and individual decision making over risk and time

5.1: Introduction

The private and social cost of obesity is potentially very high, and it is therefore important to obtain a better understanding of the behavioral factors that may lead to healthier lifestyles. The decision to obtain and maintain a healthy score in the BMI involves a tradeoff between personal gratifications from unhealthy lifestyles in the short term that lead to uncertain negative health effects in the longer term. People with a high BMI score would thus appear to be less risk averse and more impatient by putting more emphasis on short-term benefits of unhealthy diets and low physical activity than those with a lower, healthy BMI. The BMI score may therefore be correlated with individual risk attitudes and discount rates, where those discount rates may be constant over time but simply higher for people who are overweight. We do not explore hyperbolic or quasi-hyperbolic discounting within our research. Hyperbolic discounting refers to the tendency for individuals to choose a smaller, sooner reward over a longer, later reward as the delay occurs sooner rather than later in time (Loewenstein and O'Donoghue, 2002). Whilst of interest our data does not allow for such investigations.

We use data from a field experiment in Denmark that allows a direct characterization of individual risk attitudes and discount rates. Using the terminology of Harrison and List (2010) the experiment can be classified as an "artefactual field experiment".[48] The experimental design is documented in detail by Harrison et al. (2005). A summarized version of project and data collection is outlined here.

[48] Harrison and List [2004; p.1014] define an artefactual field experiment as "… a conventional lab experiment but with a nonstandard subject pool."

Sampling Procedures

The sample was designed to be representative of the adult Danish population between 19 and 75 years of age in January 2003 and stratified according to the size of the population in each county. To achieve this, the construction of the sample consisted of six steps:

1. A random sample of 25,000 Danes aged between 19 and 75 was drawn from the Danish Civil Registration Office.
2. 493 individuals (<2% of the sample) were excluded from the sample due to the extraordinarily remote location of residence.
3. Each county was assigned either 1 session or 2 sessions, in rough proportionality to the population of the county resulting in 20 sessions.
4. Due to geographical size, six counties were divided into two sub-groups. One of the two subgroups was then randomly selected as the location for the sessions.
5. The first 30 or 60 randomly sorted records were selected within each county, depending on the number of sessions allocated to that county. This provided a sub-sample of 600.
6. Invitations to attend were posted to the sample of 600. Where response rates were low 64 further invitations were posted to newly drawn individuals. Each individual that gave a positive response was assigned to a session. The recruited sample was 268.

The experiments were conducted in June 2003 with a total of 253 participants.

Conduct of the Sessions

The sessions were conducted in convenient locations across Denmark. The sessions lasted 2 hours and participants met in groups of no more than 10. A laptop was provided to each participant, on which the experimental program ran. Each subject was identified by a unique ID number and results for each participant were downloaded onto their laptop following the session which allowed the experiments to be conducted without networking the computers. Participants were paid 500 DKK for completion of the experiment or 100 DKK if they were not able to stay for the full session.

Instructions for the experiment were provided on the computer screens, and subjects read through the instructions while the experimenter read them aloud. Following the instructions the experiment was conducted in three parts:

1. A sociodemographic questionnaire.
2. Four risk aversion tasks.
3. Six discount rate tasks.

The four risk aversion tasks and the six discount rate tasks are described in more detail in Section 5.6.

Prior to the risk aversion task a significant amount of time was spent explaining the logic of the approach, verifying that subjects were able to correctly fill in the tasks and illustrating the random procedures necessary to reach a final lottery outcome for each possible choice within the tasks.

Following the risk aversion tasks and the discount rate tasks one task and one row from each task were picked at random for payment, and each subject was given a 10% chance to actually receive the payment associated with his or her decision. For these randomization procedures, two bingo cages were used, one containing 100 balls and the other containing 3 to 11 balls, depending on the number of decision rows in the tasks. A 10-sided die was used to determine payment. Any subject who received a roll of "0" received actual payment according to that final outcome. All payments were made at the end of the experiment.

A separate questionnaire was posted to the same 253 participants in June 2005, in which they were asked to provide information on their height, weight, presence of stress symptoms, voting activity, political views, happiness and satisfaction with life. A total of 154 subjects returned the questionnaire. Data on self-reported height and weight was used to calculate BMI for each respondent.[49] The sample of 154 subjects is divided across 80 women and 74 men, with 29 (36.3%) reported overweight among the women in the sample and 50 (67.6%) overweight among the men. The different propensity of being overweight between men and women mirrors the findings of the Danish Health Interview Survey (2000), but we observe a higher prevalence rate for both men and women in our sample, which is consistent with the global upward trend in BMI since 1980 (Finucane et al., 2011). Our statistical estimates are corrected for endogenous sample attrition, which is present in virtually any longitudinal experiment or survey that allows subjects to drop out of the panel.

[49] The potential inaccuracy of self-reported measures for height and weight is acknowledged in the literature. It is generally agreed that individuals overestimate height and underestimate weight, however, there is little agreement regarding the extent of these errors and the potential method of correction (see, Nyholm, Gullberg, Merlo, Lundqvist-Persson, Råstam and Lindblad [2007], Spencer, Appleby, Davey and Key [2002], and Faeh and Bopp [2009]).

The experimental procedures in the Danish field experiment build on the risk aversion experiments of Holt and Laury (2002) and Harrison, Lau and Rutström (2007) and the discount rate experiments of Coller and Williams (1999) and Harrison, Lau, and Williams (2002). The statistical specification follows Andersen, Harrison, Lau, and Rutström (2008a), and we use FIML to control for the curvature of the utility function in the estimation of individual discount rates. The relationship between risk and time preferences is initially specified by an exponential discount function and an explicit utility function that exhibits constant relative risk aversion (CRRA). The model is then extended to allow for subjective probability weighting and we draw inferences about probability “optimism” and “pessimism.”

5.2: Justification

Throughout this thesis we have presented a requirement for research to explore and understand theoretically grounded psychological and behavioural variables associated with obesity. Whilst previous chapters have discussed such concepts, this chapter empirically explores ‘non-rational’ drivers of behaviour in the form of the relationship between risk and time preference and BMI. Further, several limitations of the previous literature, including elicitation methods and analytical approaches, have been identified providing justification for our approach. We outline these limitations in this section and provide details on how we overcome them.

Reflecting back to the Foresight Map (see Figure 1.1), the prevalence of obesity can be attributed to a broad range of factors. Whilst acknowledging this complex system, some have argued for the importance of time preference in decisions making processes which can result in overconsumption and physical inactivity (Komlos et al. 2004). Much of the current research has examined the relationship between obesity and time preference using ‘preference proxies’ (Lawless, Drichoutis and Nayga, 2013), such as, credit card debt (Blaylock et al. 1999) and personal savings (Komlos et al. 2004). The culmination of this evidence supports the hypothesised relationship between time preference and obesity, however, due to the use of preference proxies the evidence lacks the ability to distinguish between a causal relationship and parallel trends (Komlos et al.2004) and cannot explore relationships between time preference and obesity within subgroups (e.g. older individuals) (Komlos et al.2004). The first point of justification is, therefore, the relative lack of research which study obesity through an elicitation of individual’s discount rates.

Despite the theoretical importance of risk preferences in decision making (Anderson and Mellor, 2008), there is also a lack of research exploring the relationship between risk preferences and obesity (Srinivas, 2016). The literature review, presented in Section 5.5, identifies only three studies which explore risk preferences and obesity. Our research, therefore, represents a significant contribution to the literature.

The next point of justification concerns the joint elicitation of time and risk preferences. Previous research has often assumed risk neutrality when assessing discount rates; however, we know that individuals are largely risk. The consequence of this assumption is a significant upward bias in estimated discount rates. Whilst the literature acknowledges this bias, very few address the joint elicitation of risk and time preferences directly (Andersen, Harrison, Lau, and Rutström, 2008). Of the few studies that exist, to our knowledge, none study jointly elicited risk and time preference and BMI. By employing the approach of Andersen, Harrison, Lau, and Rutström (2008), the research presented in this chapter present a significant contribution to the literature in term of analytical advancements.

A further analytical advancement is the use of statistical techniques to control for issues of sample selection. The problem of sample selection arises due to non-randomly selected samples resulting in missing data on the dependant variable within analyses (Heckman, 1977). We have previously discussed endogenous sample selection in Chapter 2. Resulting estimated parameters from regression analyses with non-random samples are likely to be biased by the probability that an observation enters the sample (Heckman, 1977). In the current literature regarding time and risk preference and obesity (see Section 5.5) no studies have controlled for sample selection. Other advancements, discussed in more detail in this chapter, include the application of Rank Dependent Utility (RDU) theory to explore risk preference specifications and the allowance of behavioural error in further detail.

The final point of justification concerns the lack of research utilising real monetary payment within experiments. The literature review provided in Section 5.5 only presents studies which have utilised real financial payments, partly explaining why so few are identified. The importance of real monetary payments is highlighted by Coller and Williams (1999) and Holt and Laury (2002) who find the estimated mean and variance of discount rates and risk preferences over monetary outcomes are significantly lower in the treatment with real monetary payments compared to a treatment with hypothetical outcomes and conclude that "*subjects facing hypothetical choices cannot imagine how they would actually behave under high-incentive conditions.*" (Holt and Laury, 2002).

To summarise discussions, there is much interest from a theoretical perspective regarding the relationship between time and risk preference and BMI, however, little empirical evidence exists. Further, the evidence that does exist is limited in the analytical approaches employed which may have produced biased estimates.

5.3: Hypothesis

We elicit measures of individual discount rates from a representative sample of the Danish population and test two substantive hypotheses. The first hypothesis is that overweight subjects are less risk averse than those with a healthy weight, where overweight is measured by a BMI score of 25 or more.[50] The second hypothesis is that overweight subjects have higher discount rates than subjects with a healthy weight.

5.4: Theoretical underpinning

We define the discount factor for a given time period τ to be the scalar D that equates the utility of a smaller level of income y received at time t with a larger level of income Y received at time t+τ, for some utility function U(.), y < Y, and given amounts y and Y. We assume that the same utility function is used to evaluate income at time t and income at time t+τ; we discuss this assumption later. This general definition of D permits the special case, much studied in the experimental literature, in which U(.) is linear. The non-linear case is of great empirical significance for inferences about discount rates, as demonstrated by Andersen, Harrison, Lau and Rutström (2008). There is nothing in this definition of the discount factor that restricts us to Expected Utility Theory (EUT), and indeed alternative

[50] Four subjects in our sample have a BMI score below 18.5, which is medically considered "under-weight." For the purpose of this study "healthy weight" refers to all subjects with a BMI score below 25.

rank-dependent specifications are considered later. We define utility over income and not directly over consumption flows or wealth, and discuss the implications of that specification later.

5.5: Literature review

There have only been few attempts to study the association between BMI and individual risk and time preferences using salient and incentive compatible decision tasks in the experimental design. We review the few studies with real monetary rewards in the experimental decision tasks since there is overwhelming evidence of hypothetical bias in preference elicitation, including the elicitation of individual risk attitudes and discount rates.[51]

5.5.1: Risk Attitudes and BMI

Anderson and Mellor (2008) collected data from a sample of 1,094 adult subjects in the greater Williamsburg, Virginia area. Non-students were recruited via a variety of local organizations and flyers in public places, and students were recruited from the College of William and Mary. Measures of individual risk attitudes were elicited by a multiple price list with 10 decision rows, and the basic experimental design was similar to Holt and Laury (2002). The prizes were \$6.00 and \$4.80 in lottery A, and \$11.55 and \$0.30 in lottery B. They run simple OLS regression models with self-reported BMI as a function of constant relative

[51] Coller and Williams [1999] elicit individual discount rates using multiple price lists and find that the estimated mean and variance of discount rates over monetary outcomes are significantly lower in the treatment with real monetary payments compared to a treatment with hypothetical outcomes. Holt and Laury [2002] present similar conclusions regarding real vs. hypothetical rewards in their risk aversion tasks, and state that "subjects facing hypothetical choices cannot imagine how they would actually behave under high-incentive conditions." (p. 1654).

risk aversion derived under EUT and find that overweight subjects with a BMI greater than 25 are significantly less risk averse than healthy weight subjects. This approach, however, does not consider information on the standard error of the estimated CRRA parameter in the regression model for BMI, and the estimated standard deviation of the sampling distribution for the coefficient on relative risk aversion is downward biased. Hence, the results overstate the statistical significance of the association between BMI and risk aversion.

Galizzi and Miraldo (2012) also use the multiple price list design by Holt and Laury (2002) to elicit individual risk attitudes. The subjects were presented with four multiple price lists where the prizes in the lotteries varied between £1 and £385.[52] They collect data from a sample of 120 students at the University of York and find a significant association between BMI and risk attitudes for men, but not for women. In particular, they find that overweight men are significantly less risk averse than men with healthy weight. However, there is no significant association between BMI and risk attitudes when a Healthy Eating Index is added in the analysis.[53] The statistical analysis is based on maximum likelihood estimation where the utility function is represented by a constant relative risk aversion function, and the coefficient of relative risk aversion is estimated under the assumption of EUT conditional on a self-reported measure of BMI.

Koritzky, Yechiam, Bukay and Milman (2012) use the co-called Iowa Gambling Task to elicit measures of individual risk attitudes. Subjects are asked to pick a number of cards from four

[52] The four sets of prizes were (A1: £20, £16; B1: £38.50, £1), (A2: £6, £4.80; B2: £11.55, £0.30), (A3: £200, £160; B3: £385, £10), and (A4: £40, £32; B4: £77, £2).
[53] The survey questions that comprise the index were administered during the experiment.

decks of cards. Each card yields a gain or a loss and the subjects are not informed about the number of trials (100) in the decision task or the allocation of gains and losses in the four decks. There are two disadvantageous and two advantageous decks of cards. In the two disadvantageous decks each card yields a sure gain of 100 (Israeli) shekel and one-in-two cards in one deck yields a loss of 250 shekel, and one-in-ten cards in the other deck yields a loss of 1250 shekel. In the two advantageous decks each card yields a sure gain of 50 shekel and one-in-two cards in one deck yields a loss of 50 shekel, and one-in-ten cards in the other deck yields a loss of 250 shekel.[54] The results suggest that overweight men engaged in excessive risk taking whereas overweight women do not have significantly different risk attitudes compared to the normal weight control group. The risk measure is based on the fraction of risky choices, and it is not clear what excessive risk taking means except that overweight men appear to be taking significantly more cards from the two disadvantageous decks. There is no attempt to transform the responses into structural measures of risk attitudes, which makes it hard to compare the findings with those based on alternative elicitation methods, or even other papers that use the Iowa Gambling Task.[55]

The results thus suggest that there may be a negative association between BMI and aversion to take financial risk, with overweight respondents being less risk averse than others. The literature has so far only looked at EUT in the representation of individual risk

[54] It is not clear whether any subjects experienced overall losses in the decision task and how the experimenters would handle a situation in which a subject experiences an overall loss.

[55] Brogan, Hevey, O'Callaghan, Yodor and O'Shea [2009] use a similar Iowa Gambling Task but the decision task is not incentive compatible: the subject with the highest payoff in the decision task at the session earns a bonus of $100, the other subjects earn nothing apart from a fixed recruitment fee that is paid to all subjects. Pignatti et al. [2006] and Brogan, Hevey and Pignatti [2011] also use the Iowa Gambling Task to measure individual risk attitudes, but the decision tasks are not incentivized.

attitudes and does not consider alternative models of choice under uncertainty such as Rank-Dependent Utility Theory that allow for subjective probability weighting.

5.5.2: Discounting and BMI

There has been much focus on the association between individual discounting and risky behaviour with potential negative long term health outcomes, but there are surprisingly few studies that link observations from decision tasks with real incentives to information on BMI. We have come across three papers that study the association between BMI and individual discounting using real incentives in the behavioural decision tasks.[56]

Chabris et al. (2008) conducted three related experiments in which they study the association between individual discount rates and risky health related behaviour, including BMI. Their “Weight Study” (n=126)[57] and “Cognitive Study” (n=136) recruited subjects from the Greater Boston area via public advertisements and invited them to participate in laboratory sessions to complete the experiment. The “Web Study” (n=422) recruited subjects via the internet and invited them to complete the experiment online. All subjects were asked to make decisions in 27 binary choice tasks that are used to elicit discount rates. The experimental tasks follow the design by Kirby, Petry and Bickel (1999), and the early payment option is always presented to the subject as an immediate payment, although cheques were actually mailed to subjects approximately two weeks after the session. The

[56] Kirby et al. [2002] study the correlation between discount rates and BMI using a sample of 154 Tsimane’ Amerindians in Bolivia. The subjects are presented with the same 8 binary choice tasks with monetary rewards to elicit individual discount rates. The time horizon is different in each task and varies between 7 and 157 days, and one cannot estimate discount rates for any single time period with this design. Estimates of preferences with declining discount rates, which they attempt, are therefore highly unreliable, and we have chosen to exclude the study from the review.

[57] This study was mainly concerned with the relationship between BMI and measures of impulsive behavior, and the subjects were therefore asked to fast 12 hours before they participated in the experiment.

delay to the later payment varies between 7 and 186 days, and is interpreted as the time horizon between the two payments in the statistical analysis.[58] Height and weight were measured during the experiment in the Weight Study and are self-reported in the Cognitive Study and Web Study. Time preferences are represented by a one-parameter hyperbolic discounting function, which by definition implies that individual discount rates decline over time. They run simple OLS regression models with BMI as the dependent variable and condition the model on estimated discount rates from a separate OLS regression model. They find a significant positive correlation between BMI and estimated discount rates: a higher BMI is associated with less patience in financial terms. However, the statistical significance of this association may be compromised by the LIML procedure that the statistical approach relies on.

Richards and Hamilton (2012) studied responses from a sample of 82 undergraduate students at Arizona State University. They used the elicitation method of Becker, DeGroot, and Marschak (1964) and asked subjects to state the certain amount today that is equally preferred to a certain later amount. For example, the subject may be asked to state the amount today that is equally preferred to a payment of £10 tomorrow. The subjects were asked to make decisions in 2 sets of 25 tasks. The later amount was fixed in one set of tasks, and the sooner amount was fixed in the other set. The fixed amount varied between $1 and $100, and the time horizon between the sooner and later amounts varied between one day and one year. The statistical analysis relies on maximum simulated likelihood estimation of a random preference specification. They estimated a flexible inter-temporal model that nests

[58] They do not mention how long it took to mail the delayed payments to subjects, and it is not clear what precise time periods the subjects responded to: the actual payment dates, the expected payment dates, or the dates posed to them in the instructions.

exponential, quasi-hyperbolic and hyperbolic discounting functions and control for the curvature of the utility function. Their results also point to a significant positive correlation between individual discount rates and obesity. Despite using a flexible discounting function, they only condition the exponential part of the discounting function on BMI. Hence, one cannot make inferences about the association between BMI and inter-temporal inconsistency measured by quasi-hyperbolic and/or hyperbolic discounting function.[59]

Finally, Budría, Lacomba, Lagos and Swedberg (2012) use a sample of 41 subjects, where 26 of these subjects were recruited from the Association of Obese People (ASOFE) in Almeria, Spain. The 26 subjects had undergone surgery and were thus committed to losing weight. The control group of 15 subjects were relatives of the 26 subjects in the study group with the intent to obtain similar demographic characteristics. Each participant was presented with 20 decisions between a sooner and a later payment option and asked to choose one option in each decision. The 20 decision tasks were presented simultaneously in a multiple price list. The sooner payment was 300 euros that was paid out one month after the experiment. The later payment varied from 303 to 469 euros and was paid out seven months after the experiment, providing a time interval of 6 months between the sooner and later payment options in the discounting tasks. The results show that the study group displayed significantly lower discount rates than the control group, most likely because the study group were committed to focus on long-term health effects that may have spilled over to choices over delayed monetary outcomes.

[59] Richards and Hamilton [2012] use the term “present bias” to represent high discount rates between any two periods in time, including a fixed, positive monetary premium on delayed outcomes.

The results from the previous studies suggest that there is a significant negative association between individual discount rates and BMI: overweight subjects tend to be more impatient compared to control groups with normal weight. The results are robust across experiments with students and non-students, and with and without controls for the curvature of the utility function. However, there is no information on the selection processes into the experiments and one cannot assess to what extent the samples represent the general population.

5.6: Experimental design

We use data from a Danish field experiment that is documented in detail by Harrison, Lau, Rutström, and Sullivan (2005), and focus here on the basic characteristics of the experimental design. Each subject was asked to respond to 4 risk aversion tasks and 6 discount rate tasks. The tasks involved a series of binary choices, typically 10 per task. Thus each subject typically provided 40 binary choices that can be used to infer individual risk attitudes and 60 choices that can be used to infer individual discount rates.

5.6.1: Measuring Risk Aversion

Individual risk attitudes were elicited by a multiple price list design that is similar to the approach in Holt and Laury (2002).[60] The subjects were presented with an ordered array of pairs of lotteries in a table, one pair per row, and asked to indicate their preferred lottery in each row. In the first row, lottery A gave the individual a 10% chance of receiving 2,000 kroner and 90% chance of receiving 1,600 kroner, and lottery B gave a 10% chance of receiving 3,850 kroner and 90% chance of receiving 100 kroner. The probability of receiving the high outcome in each lottery increased by 10% as one moved to the next row in the MPL until the last choice was between two certain amounts of money, in this example 2,000 and 3,850 kroner. Each subject responded to four separate risk aversion tasks, each with different prizes designed so that all 16 prizes span an income interval from 50 kroner to 4,500 kroner.[61] One task and one row were picked at random for payment, and each subject

[60] Andersen, Harrison, Lau, and Rutström [2006] examine the properties of the MPL procedure in detail, and the older literature using it. Harrison and Rutström [2008] evaluate the strengths and weaknesses of alternative elicitation procedures for risk attitudes.

[61] The four sets of prizes were as follows, with the two prizes for lottery A listed first and the two prizes for lottery B listed next: (A1: 2000 kroner, 1600 kroner; B1: 3850 kroner, 100 kroner), (A2: 2250 kroner, 1500 kroner; B2: 4000 kroner, 500 kroner), (A3: 2000 kroner, 1750 kroner; B3: 4000 kroner, 150 kroner), and (A4: 2500 kroner, 1000 kroner; B4: 4500 kroner, 50 kroner). At the time of the experiments, the exchange rate was approximately 6.55 kroner per U.S. dollar, so these prizes range from approximately $7.65 to $687.

was given a 10% chance to actually receive the payment associated with his or her decision.[62]

We take each of the binary choices of the subject as the data, and estimate the parameters of a latent utility function that explains those choices using an appropriate error structure to account for the panel nature of the data. The data set consists of 7,928 observations from 253 subjects.[63] Once the utility function is defined, for a candidate value of the parameters of that function, we can construct the expected utility of the two lotteries, and then use a linking function to infer the likelihood of the observed choice.

5.6.2: Measuring Discount Rates

The basic experimental design for eliciting individual discount rates was introduced in Coller and Williams (1999) and expanded in Harrison, Lau, and Williams (2002). Each subject was presented with 6 discount rate tasks with different time horizons: 1 month, 4 months, 6 months, 12 months, 18 months, and 24 months. In each task they were asked to choose between two future income options rather than one "instant income" option or one future income option. The early income option was 3,000 kroner and delayed by one month in all tasks. For example, they were offered 3,000 kroner in one month and 3,000 kroner + *x*

[62] There is some evidence that rewarding subjects by selecting one task at random for payment does not distort choices under Expected Utility Theory, even though it does make the overall experiment a compound lottery, see Harrison, Lau, and Rutström [2007; fn.16] and Harrison and Rutström [2008; §2.6]. On the other hand, there is some evidence that this random lottery protocol can affect inferences about risk preferences under Rank-Dependent Utility Theory, see Harrison and Swarthout [2012]. The reason is that the payment protocol relies on the independence axiom, which is a maintained assumption under Expected Utility Theory, but relaxed under Rank-Dependent Utility Theory. We assume here that the payment protocol does not influence inferred risk attitudes.

[63] Some subjects received a different number of choices than others. 116 subjects received a "symmetric" risk aversion task involving 40 choices (hence there were 116×40 = 4,640 choices) and the remaining 137 subjects received an "asymmetric" risk aversion task involving 24 choices (hence there were 137×24 = 3,288 choices), see Harrison Lau, Rutström and Sullivan [2005] for details.

kroner in seven months, so that we interpret the revealed discount rate as applying to a time horizon of six months. This avoids the potential problem of the subject facing extra risk or transactions costs with the future income option, as compared to the "instant" income option.[64] However, the design implies that we cannot identify any fixed risk premium that subjects may require to delay a monetary reward, which rules out the popular quasi-hyperbolic discounting function by Phelps and Pollack (1968) and Laibson (1997), and the fixed-cost specification by Benhabib, Bisin and Schotter (2010).

Each subject responded to all six discount rate tasks and one task and row were chosen at random for payment. Future payments to subjects were guaranteed by the Danish Ministry of Economic and Business Affairs, and made by automatic transfer from the Ministry's bank account to the subject's bank account. This payment procedure is similar to a post-dated check, and automatic transfers between bank accounts are a common procedure in Denmark. Finally, each subject was given a 10% chance to receive actual payment. Thus, each subject had a 10% chance of being paid for one of the risk aversion tasks and a 10% chance of being paid for one of the discount rate tasks.

Our estimation strategy is the same as for the lottery task. We take each of the binary choices of the subject as data, and estimate the parameters with an error structure that recognizes the panel nature of the data and allows for clustered standard errors at the level of the individual. Individual risk attitudes and discount rates are estimated jointly, where the choices over lotteries are used to identify individual risk attitudes and the choices over

[64] These transactions costs are discussed in Coller and Williams [1999], and they include simple things such as remembering to pick up the delayed payment as well as more complex things such as the credibility of the money actually being paid in the future. The payment protocol in the experiment was intended to make sure that the credibility of receiving the money in the future was high.

deferred payments are used to identify individual discount rates, conditional on the curvature of the utility function. The data set consists of 15,180 discount rate choices from 253 subjects.

Finally, a socio-demographic questionnaire was administered to subjects and information was collected on age, sex, size of town the subject resided in, type of residence, primary occupation during the last 12 months, highest level of education, household type (viz., marital status and presence of younger or older children), number of people employed in the household, total household income before taxes, whether the subject is a smoker, and the number of cigarettes smoked per day.

5.7: Econometric specification

We first write out a structural model to estimate risk attitudes assuming EUT. We then expand the model to control for sample selection, and discuss how the model is extended to allow for the RDU model with non-linear utility and probability weighting. Finally, the model is extended to allow for joint estimation of individual risk attitudes and exponential discounting with controls for sample selection.

5.7.1: Estimating the Utility Function

Consider the identification of risk preferences in the simple EUT model of decision-making under risk, without controlling for sample selection. Assume for the moment that utility of income M is defined by the CRRA specification

$$U(M) = M^{(1-r)}/(1-r) \qquad (1)$$

where M is the lottery prize and $r \neq 1$ is a parameter to be estimated. Thus r is the coefficient of constant relative risk aversion: $r=0$ corresponds to risk neutrality, $r<0$ denotes risk seeking behavior, and $r>0$ denotes risk aversion. Let there be two possible outcomes in a lottery. Under EUT the probabilities for each monetary outcome M_j, $p(M_j)$, are those that are induced by the experimenter, so expected utility is simply the probability weighted utility of each outcome in lottery i:

$$EU_i = [\ p(M_1) \times U(M_1)\ ] + [\ p(M_2) \times U(M_2)\ ] \qquad (2)$$

The Expected Utility (EU) for each lottery pair is derived for a candidate estimate of r, and the index

$$\nabla EU = EU_B - EU_A \qquad (3)$$

is calculated, where EU_A is option A and EU_B is option B as presented to subjects. This latent index, based on latent preferences, is then linked to observed choices using the cumulative logistic distribution function $\Lambda(\nabla EU)$. This "logit" function takes any argument between $\pm\infty$ and transforms it into a number between 0 and 1. The logit link function is:

$$\text{prob(choose lottery B)} = \Lambda(\nabla EU) \qquad (4)$$

The index defined by (3) is linked to the observed choices by specifying that the B lottery is chosen when $\Lambda(\nabla EU)>\frac{1}{2}$, which is implied by the logistic function in (4).

Thus the likelihood of the observed responses, conditional on the EUT and CRRA specifications being true, depends on the estimates of r given the above statistical specification and the observed choices. The conditional log-likelihood is then

$$\ln L(r; y, \mathbf{X}) = \textstyle\sum_i [\ (\ln \Lambda(\nabla EU)\times\mathbf{I}(y_i = 1)) + (\ln (1-\Lambda(\nabla EU))\times\mathbf{I}(y_i = -1))\ ] \qquad (5)$$

where $\mathbf{I}(\cdot)$ is the indicator function, y_i =1(−1) denotes the choice of the Option B (A) lottery in risk aversion task i, and **X** is a vector of treatments and individual characteristics. The parameter r is defined as a linear function of the characteristics in vector **X**.[65]

An important extension of the core model is to allow for subjects to make some errors. The notion of error is one that has already been encountered in the form of the statistical assumption that the probability of choosing a lottery is not 1 when the EU of that lottery exceeds the EU of the other lottery. This assumption is clear in the use of a link function between the latent index ∇EU and the probability of picking one or the other lottery; in the case of the logistic cumulative distribution function, this link function is Λ(∇EU). If there were no errors from the perspective of EUT, this function would be a step function: zero for all values of ∇EU<0, anywhere between 0 and 1 for ∇EU=0, and 1 for all values of ∇EU>0.

We allow for "behavioral errors" using a specification originally due to Fechner and used by Hey and Orme [1994], among others. This behavioral error specification posits the latent index

$$\nabla EU = (EU_B - EU_A)/\mu \qquad (3')$$

instead of (3), where μ is a structural "noise parameter" used to allow some flexibility in the specification of the error terms from the perspective of the deterministic EUT model. This is just one of several different types of error story that one can use, and Wilcox (2008)

[65] Andersen, Harrison, Lau and Rutström [2010] review statistical procedures that can be used to estimate structural models of this kind, as well as more complex non-EUT models. It is a simple matter to correct for stratified survey responses, multiple responses from the same subject ("clustering"), or heteroskedasticity, as needed.

provides a review of the implications of the alternatives.[66] As the error term μ goes towards 0 this specification collapses to the deterministic choice EUT model, where the choice is strictly determined by the EU of the two lotteries; but as μ gets larger and larger the choice essentially becomes random. Thus μ can be viewed as a parameter that flattens the link function as it gets larger.

The likelihood of the risk aversion task responses, conditional on the EUT and CRRA specifications being true, depends on the estimates of r and μ. The conditional log-likelihood is

$$\ln L^{EUT}(r, \mu; y, \mathbf{X}) = \sum_i \left[(\ln \Lambda(\nabla EU) \times \mathbf{I}(y_i=1)) + (\ln (1-\Lambda(\nabla EU)) \times \mathbf{I}(y_i=-1)) \right] \tag{6}$$

where $y_i = 1(-1)$ denotes the choice of Option B (A) in risk aversion task i, and **X** is a vector of individual characteristics.

5.7.2: Statistical Correction for Sample Selection

The experimental design allows us to correct for sample selection into the survey. We recognize that there may be some sample selection issues in the longitudinal setting that affects the risk aversion estimates. Selection bias would arise if subjects condition their participation in the experiment on unobservable characteristics that are correlated with their risk attitudes.

[66] Some specifications place the error at the final choice between lotteries or after the subject has decided which one has the higher expected utility; some place the error earlier, on the comparison of preferences leading to the choice; and some place the error even earlier, on the determination of the expected utility of each lottery.

To control for selection bias into the survey component in which we obtain information on BMI, we use observations from the initial sample of 253 subjects in the experiment and condition the selection parameter on self-reported individual socio-demographic characteristics. We employ the "direct likelihood" approach of Heckman (1976), Hausman and Wise (1979) and Diggle and Kenward (1994), *inter alia*. The conditional log-likelihood is now written as

$$\ln L^{EUT}(r, \mu, \tau, \rho_{RA}; y, \mathbf{X}) = \sum_i [(\ln \Phi(\tau, \nabla EU)\times\mathbf{I}(z_i = 1)) + (\ln \Phi(-\tau)\times\mathbf{I}(z_i = -1))] \tag{7}$$

where z_i =1(−1) denotes selection into the survey, $\Phi(\tau, \nabla EU)$ is a bivariate normal cumulative distribution of the selection parameter τ and the latent index ∇EU, and ρ_{RA} is the correlation coefficient between τ and ∇EU. The first term on the right-hand side of equation (6) is the contribution to the likelihood function from subjects who participated in the survey, and the second term is the likelihood contribution from those subjects who rejected the invitation to answer the questions in the survey.

The FIML specification in (7) jointly estimates two probit models with a bivariate normal distribution of the error terms in the two equations. The two probit models estimate the constant relative risk aversion function (main equation) and selection into the survey (selection equation). The estimated coefficients or r and μ in the main equation are not biased if selection into the survey is random, i.e. when ρ_{RA} is equal to 0. However, the estimated coefficients in the main equation are biased when ρ_{RA} is different from 0, and the joint estimation of the two probit models in (7) controls for selection bias using a parametric (bivariate normal) specification of the association between the two error terms.

The specification is identical to the usual specification of a probit model with sample selection. In that case the probit equation of interest (main equation) has the linear latent form $y^* = x\beta + u_1$, where x denotes observables and β denotes parameters. We observe the binary outcome 1 if $y^* > 0$ and we observe the binary outcome 0 if $y^* \leq 0$. The (probit) selection equation has the linear latent form $z^* = w\gamma + u_2$, where w denotes observables and γ denotes parameters. We observe the sample in the first equation if $z^* > 0$, and otherwise we do not observe the sample. Assuming that $u_1 \sim N(0,1)$, $u_2 \sim N(0,1)$ and that the correlation of u_1 and u_2 is ρ, the sample selection model estimates β, γ and ρ. If $\rho \neq 0$, then direct estimation of the first probit model (main equation) would yield biased results. It is noteworthy that the first formal statement of the probit model with sample selection also considered the case in which the latent index was the difference in expected utility from two outcomes, which we denote by ∇EU: see Van de Ven, Wynard and Van Praag (1981; p. 235, equation (8)).

5.7.3: Estimating Subjective Optimism or Pessimism

We also provide estimates from a RDU model, to ascertain if subjects exhibit probability optimism or pessimism. To calculate decision weights under RDU one replaces expected utility

$$EU_i = \sum_{k=1,K} [\, p_k \times u_k \,]$$

with RDU

$$RDU_i = \sum_{k=1, K} [\ w_k \times u_k\ ], \tag{8}$$

where

$$w_i = \omega(p_i + ... + p_n) - \omega(p_{i+1} + ... + p_n) \tag{9a}$$

for i=1,... , n−1, and

$$w_i = \omega(p_i) \tag{9b}$$

for i=n, where the subscript indicates outcomes ranked from worst (i=1) to best (i=n), and ω(p) is a probability weighting function. Hence, the actual probabilities under EUT are replaced by decision weights under RDU that are determined by the ranking of outcomes and non-linear transformation of cumulative probabilities over outcomes.

Picking the right probability weighting function is obviously important for RDU specifications. The simplest specification is the power function

$$\omega(p) = p^{\eta} \tag{10}$$

This probability weighting function is useful pedagogically, since values of η>1 implies pessimism with respect to lottery probabilities, and values of η<1 implies optimism. *Ceteris paribus* the utility function curvature, estimates of η<1 provide an additional psychological source for a positive risk premium (since better prizes are given lower decision weight than their objective probabilities, and poorer prizes are given higher decision weight).

The "inverse-S" weighting function proposed by Tversky and Kahneman (1992) has also been widely employed. It is assumed to have well-behaved endpoints such that $\omega(0)=0$ and $\omega(1)=1$ and to imply weights

$$\omega(p) = p^{\gamma}/[\, p^{\gamma} + (1-p)^{\gamma}\,]^{1/\gamma} \tag{11}$$

for $0<p<1$. The normal assumption in the empirical literature, reviewed by Gonzalez and Wu (1999), is that $0<\gamma<1$. This gives the weighting function an "inverse S-shape," characterized by a concave section signifying the overweighting of small probabilities up to a crossover-point where $\omega(p)=p$, beyond which there is then a convex section signifying underweighting. Hence this specification with $\gamma<1$, implies, again *ceteris paribus* the curvature of the utility function, optimism or risk-loving with respect to small objective probabilities and pessimism or risk aversion with respect to larger objective probabilities. If $\gamma>1$ the function takes the less conventional "S-shape," with convexity for smaller probabilities and concavity for larger probabilities. Nothing in the *theory* of the RDU model requires $\gamma<1$.

Finally, Prelec (1998) presents a flexible two-parameter probability weighting function that includes (10) and (11) as special cases. This function is written as

$$\omega(p) = \exp\{-\eta(-\ln(p))^{\phi}\} \tag{12}$$

and is defined for $0<p<1$, $\eta>0$ and $\phi>0$. We use this flexible specification in our statistical model of RDU, and the conditional log-likelihood is now written as

$$\ln L^{RDU}(r, \eta, \phi, \mu, \tau, \rho_{RA}; y, \mathbf{X}) = \sum_i [(\ln \Phi(\tau, \nabla EU)\times\mathbf{I}(z_i = 1)) + (\ln \Phi(-\tau)\times\mathbf{I}(z_i = -1))] \qquad (13)$$

where η and ϕ are additional parameters to be estimated compared to the EUT model.

5.7.4: Estimating the Discounting Function

Assume that the discounting function is exponential. A subject is indifferent between two income options M_t and $M_{t+\tau}$ if and only if

$$(1/(1+\delta)^t)\ U(M_t) = (1/(1+\delta)^{t+\tau})\ U(M_{t+\tau}) \qquad (14)$$

where $U(M_t)$ is the utility of monetary outcome M_t for delivery at time t, δ is the discount rate, τ is the horizon for delivery of the later monetary outcome at time t+τ, and the utility function U is separable and stationary over time. The left hand side of equation (14) is the discounted utility of receiving the monetary outcome M_t at time t, and the right hand side is the discounted utility of receiving the outcome $M_{t+\tau}$ at time t+τ. Thus δ is the discount rate that equalizes the present value of the utility of the two monetary outcomes M_t and $M_{t+\tau}$ discounted to t=0.

We can write out the likelihood function for the choices that our subjects made and jointly estimate the risk parameter r in equation (1), the probability weighting parameters η and ϕ in (12), and the discount rate parameter δ in (14). We use the same stochastic error specification as in (3'), albeit with a different Fechner error term υ for the discount choices:

$$\nabla PV = (PV_B - PV_A)/\upsilon \tag{15}$$

where the discounted utility of Option A is given by

$$PV_A = (1/(1+\delta)^t)(M_A)^{(1-r)}/(1\text{-}r) \tag{16}$$

and the discounted utility of Option B is

$$PV_B = (1/(1+\delta)^{t+\tau})\,(M_B)^{(1-r)}/(1\text{-}r) \tag{17}$$

and M_A and M_B are the monetary amounts in the choice tasks presented to subjects.

We assume here that the utility function is stable over time and is perceived *ex ante* to be stable over time. Evidence for the former proposition is provided by Andersen, Harrison, Lau and Rutström (2008), who examine the temporal stability of risk attitudes in the Danish population. The second proposition is a more delicate matter: even if utility functions are stable over time, they may not be subjectively perceived to be, and that is what matters for us to assume that the same r that appears in (1) appears in (16) and (17). When there is no front end delay, this assumption is immediate for (16), but not otherwise. These two assumptions regarding the stability of utility functions are common in the empirical literature on inter-temporal choice and allow us to map responses in the decision tasks to observations from the survey component that was administered two years after the experiment.[67]

Thus the likelihood of the discount rate responses, conditional on the CRRA and exponential discounting specifications being true, depends on the estimates of r, δ, and υ, given the observed choices. The conditional log-likelihood is

$$\ln L^{IDR}(r, \delta, \upsilon, \tau, \rho_{IDR}; y, \mathbf{X}) = \sum_i [(\ln \Phi(\tau, \nabla PV)\times\mathbf{I}(z_i = 1)) + (\ln \Phi(-\tau)\times\mathbf{I}(z_i = -1))] \quad (18)$$

where y_i =1(−1) denotes the choice of Option B (A) in discount rate task i, $\Phi(\tau, \nabla PV)$ is a bivariate normal cumulative distribution of the selection parameter τ and the latent index ∇PV, and ρ_{IDR} is the correlation coefficient between τ and ∇PV.

The joint likelihood of the responses in the risk aversion and discount rate tasks is then

$$\ln L (r, \eta, \phi, \delta, \mu, \upsilon, \tau, \rho_{RA}, \rho_{IDR}; y, \mathbf{X}) = \ln L^{RDU} + \ln L^{IDR} \quad (19)$$

where L^{RDU} is defined by (13) and L^{IDR} is defined by (18). This expression can then be maximized using standard numerical methods.

[67] We also assume that the discounting function is stable over the two-year time horizon in the experiment, which is supported by the results in Andersen, Harrison, Lau and Rutström [2008]. They use a mixture model of exponential and hyperbolic discounting functions and find that 72% of the responses in the decision tasks can be characterized as being generated from an exponential discounting function and the remaining 28% of responses are generated by a hyperbolic discounting function.

5.8: Identification Strategy

Previously, Section 4.5 outlined the identification strategy for the models of presented in Chapter 4. Discussions focused on the potential consequence of the assumption of non-linearity of the inverse Mills ratio which is used as a correction factor within sample selection models. Whilst the inclusion of the same vectors of regressors within the selection and main equations of such models is theoretically sound, as discussed, models utilising this approach may run into numerical problems due to multicollinearity. As also previously presented, a common solution to avoidance of this problem is to incorporate exclusion restrictions i.e. the identification of a variable which directly effects selection but not the outcome variable in the main equation, and the inclusion of this variable as an explanatory variable in the selection but not the main equation. Exclusion restrictions were not applied in models in Chapter 4 due to an inability to identify an appropriate and feasibly obtainable variable. Despite this we clearly state that, if a theoretically appropriate variable is identified and can be incorporated into models as an exclusion restriction, this approach is favourable. We have, thus, applied this approach in this chapter utilising a number of demographic and geographic variables.

5.9: Results

We use maximum likelihood estimation of structural models of the latent decision process, in which the core parameters that define individual risk attitudes and discount rates are estimated. The approach is an extension of the full maximum likelihood specification used in Andersen, Harrison, Lau, and Rutström (2008a) with modifications for alternative probability weighting functions. We also exploit that we know certain characteristics of the sample and correct for selection bias using well-known statistical methods. As previously discussed, the classic problem of sample selection refers to possible recruitment biases, such that the observed sample is generated by a process that depends on the nature of the experiment. We focus on possible attrition bias and take the sample of 253 subjects in the experiment as the population, and use the elicited information on individual characteristics to control for selection into the later survey component with 154 respondents.

Table 5.1 provides definitions of the variables used in the statistical analysis and summary statistics. It is clear that the data set is different from standard samples of students in laboratory experiments and more representative of the adult Danish population. The share of men and women is the same in the two samples, but the share of subjects who are older than 40 years of age is higher in the survey compared to the experiment. We also observe a higher share of subjects who own their home in the survey compared to the experiment.

Variable	Definition	Sample Mean Experiment	Sample Mean Survey
overweight	BMI ≥25	n/a	0.51
female	Female	0.51	0.52
older	Aged over 40	0.65	0.74
single	Lives alone	0.20	0.16
kids	Has children	0.28	0.29
owner	Owns home	0.69	0.79
skilled	Some post-secondary education	0.38	0.38
longedu	Substantial higher education	0.36	0.36
IncLow	Lower level income	0.34	0.29
IncHigh	Higher level income	0.34	0.38
Region_2	Lives in Copenhagen area	0.32	0.32
Region_3	Lives in a city of 20,000 or more	0.45	0.45
	Number of subjects	253	154

Table 5.1: List of Variables and Descriptive Statistics

NOTE: Most variables have self-evident definitions. The omitted age group is 30-39. Variable "skilled" indicates if the subject has completed vocational education and training or "short-cycle" higher education, and variable "longedu" indicates the completion of "medium-cycle" higher education or "long-cycle" higher education. These terms for the cycle of education are commonly used by Danes (most short-cycle higher education program last for less than 2 years; medium-cycle higher education lasts 3 to 4 years, and includes training for occupations such as a journalist, primary and lower secondary school teacher, nursery and kindergarten teacher, and ordinary nurse; long-cycle higher education typically lasts 5 years and is offered at Denmark's five ordinary universities, at the business schools and various other institutions such as the Technical University of Denmark, the schools of the Royal Danish Academy of Fine Arts, the Academies of Music, the Schools of Architecture and the Royal Danish School of Pharmacy). Lower incomes are defined in variable "IncLow" by a household income in 2002 below 300,000 kroner. Higher incomes are defined in variable "IncHigh" by a household income of 500,000 kroner or more. The omitted region is

Københavns and Frederiksberg Kommune and Københavns Amt, where “Kommune” means municipality and “Amt” means county. The variable “Region_2” includes Frederiksborg Amt, Roskilde Amt, Vestsjællands Amt and Fyns Amt; and the variable “Region_3” includes Sønderjyllands Amt, Ribe Amt, Vejle Amt, Ringkøbing Amt, Aarhus Amt and Nordjyllands Amt.

5.9.1: Risk Attitudes

Table 5.2 shows maximum likelihood estimates of individual risk attitudes assuming EUT and CRRA. Because obesity rates of men and women are different, we consider interactions between BMI and sex and formally test for the absence of interaction effects. The estimates control for sample attrition by jointly estimating a selection equation and the main CRRA equation assuming a bivariate normal distribution of the error terms in the two equations. We also adjust for the possibility of correlation between responses from the same subject.[68]

[68] It is a simple matter to correct for stratified survey responses, multiple responses from the same subject (“clustering”), or heteroskedasticity, as needed.

	Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
			Panel A: Main Equation		
r:					
Male overweight	0.411	0.098	0.000	0.219	0.603
Male healthy weight	0.417	0.107	0.000	0.207	0.626
Female overweight	0.469	0.122	0.000	0.231	0.707
Female healthy weight	0.648	0.105	0.000	0.442	0.855
mu:					
Male overweight	0.621	0.066	0.000	0.492	0.750
Male healthy weight	0.584	0.055	0.000	0.476	0.693
Female overweight	0.730	0.090	0.000	0.554	0.907
Female healthy weight	0.673	0.063	0.000	0.549	0.797
ρ_{RA}	-0.323	0.214	0.131	-0.742	0.097
			Panel B. Selection Equation		
Constant	-0.195	0.336	0.561	-0.853	0.463
Female	0.123	0.176	0.486	-0.222	0.468
Older	0.531	0.194	0.006	0.151	0.912
Single	-0.011	0.241	0.964	-0.482	0.461
Kids	-0.104	0.219	0.633	-0.534	0.325
Owner	0.495	0.227	0.029	0.049	0.941
Skilled	-0.088	0.227	0.700	-0.533	0.358
Longed	-0.284	0.244	0.245	-0.763	0.195
IncLow	-0.144	0.222	0.514	-0.579	0.290
IncHigh	0.235	0.231	0.308	-0.217	0.687
Region_2	-0.247	0.261	0.344	-0.759	0.265
Region_3	-0.137	0.240	0.568	-0.606	0.333

Table 5.2: EUT and CRRA, Association between Sex and BMI

We do not find a significant association between risk attitudes and BMI for men or women. The estimated CRRA coefficient is 0.41 for overweight men and 0.42 for men with healthy weight, and we cannot reject the hypothesis that the two coefficients have identical values (*p*-value of 0.954). The estimated CRRA coefficient is 0.65 and 0.47 for overweight and healthy weight women, respectively. The difference in these two estimated coefficients is equal to 0.18 with a standard deviation of 0.11, and the coefficients are not significantly different (*p*-value of 0.116). There is some variation in the four estimated coefficients for the CRRA parameter, with healthy weight women in particular being more risk averse than others, and we reject the hypothesis that all coefficients have identical values using a Wald-test (*p*-value of 0.042).

The parameter ρ_{RA} measures the correlation between the residual of the sample selection equation and the residual of the main equation for individual risk attitudes. We do not find a significant correlation between responses in the risk aversion tasks and the decision to select into the survey component. The estimated correlation coefficient is -0.323 with a *p*-value of 0.131. However, we do find that older subjects and those who own their home are more likely to participate in the survey than otherwise. The estimated coefficient is 0.531 for older subjects and 0.495 for those who own their home, and the two coefficients are significantly different from 0 with reported *p*-values of 0.006 and 0.029, respectively.

Table 5.3 reports estimates for a similar model, but the binary sex variable is now replaced with a binary age variable that divides the sample into two groups: those younger than 40 years of age, and those who are older. We do not detect a statistically significant effect of BMI on estimated CRRA coefficients in each age group. However, we do find a significant effect of age on individual risk attitudes, with older subjects being less risk averse than younger subjects. The difference in estimated CRRA coefficients between younger and older subjects is 0.085 for those with healthy weight, and is 0.209 for overweight subjects. The two coefficients are significantly different from 0 with *p*-values of 0.001 and 0.032, respectively. We also reject the joint hypothesis that the estimated CRRA coefficients of the four combined age and weight groups are identical. Using a Wald-test we obtain a *p*-value of 0.054.

	Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
			Panel A: Main Equation		
r:					
Younger overweight	0.672	0.104	0.000	0.469	0.875
Younger healthy weight	0.682	0.115	0.000	0.456	0.909
Older overweight	0.463	0.094	0.000	0.279	0.647
Older healthy weight	0.597	0.096	0.000	0.409	0.785
mu:					
Younger overweight	0.363	0.051	0.000	0.263	0.462
Younger healthy weight	0.517	0.072	0.000	0.376	0.658
Older overweight	0.691	0.053	0.000	0.587	0.795
Older healthy weight	0.689	0.050	0.000	0.591	0.787
ρ_{RA}	-0.132	0.239	0.581	-0.601	0.337
			Panel B. Selection Equation		
Constant	-0.199	0.340	0.557	-0.865	0.466
Female	0.114	0.179	0.525	-0.237	0.465
Older	0.521	0.196	0.008	0.137	0.905
Single	0.000	0.244	0.999	-0.477	0.478
Kids	-0.101	0.221	0.646	-0.534	0.331
Owner	0.510	0.227	0.025	0.066	0.955
Skilled	-0.078	0.229	0.734	-0.527	0.371
Longed	-0.274	0.246	0.265	-0.757	0.208
IncLow	-0.145	0.223	0.517	-0.582	0.293
IncHigh	0.241	0.233	0.302	-0.216	0.697
Region_2	-0.259	0.266	0.329	-0.780	0.261
Region_3	-0.145	0.243	0.550	-0.621	0.330

Table 5.3: EUT and CRRA, Association between Age and BMI

Table 5.4 and Table 5.5A2 report estimated CRRA coefficients for the same two previous statistical models with no controls for selection. The correlation coefficient in Table 5.2 and Table 5.3 is negative and indicates that the estimated CRRA coefficients are smaller in the model that controls for selection compared to a similar model that does not control for selection. Table 5.4 shows that the uncorrected coefficients generally are higher than the corrected coefficients in Table 5.2, and we confirm the previous finding that there is no significant association between risk attitudes and BMI for men. However, we find that the estimated difference in CRRA between overweight and healthy weight women has a *p*-value of 0.086 and is significant at the 10% confidence level. One would thus incorrectly infer that overweight women are significantly less risk averse than healthy weight women without the statistical correction for selection into the survey component. The results in Table 5.5 confirm the findings in Table 5.3: we do not find a significant association between CRRA and BMI in the young and older age groups, respectively.

	Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r:					
Male overweight	0.511	0.055	0.000	0.402	0.619
Male healthy weight	0.511	0.077	0.000	0.359	0.662
Female overweight	0.572	0.088	0.000	0.400	0.744
Female healthy weight	0.761	0.067	0.000	0.630	0.892
mu:					
Male overweight	0.601	0.054	0.000	0.495	0.706
Male healthy weight	0.564	0.047	0.000	0.471	0.656
Female overweight	0.710	0.081	0.000	0.551	0.868
Female healthy weight	0.665	0.060	0.000	0.547	0.782

Table 5.4: EUT and CRRA, Association between Sex and BMI without Control for Selection

	Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r:					
Younger overweight	0.706	0.083	0.000	0.545	0.868
Younger healthy weight	0.731	0.078	0.000	0.578	0.884
Older overweight	0.502	0.054	0.000	0.396	0.608
Older healthy weight	0.635	0.068	0.000	0.502	0.767
mu:					
Younger overweight	0.362	0.052	0.000	0.261	0.463
Younger healthy weight	0.517	0.072	0.000	0.377	0.657
Older overweight	0.686	0.050	0.000	0.588	0.785
Older healthy weight	0.687	0.050	0.000	0.590	0.784

Table 5.5: EUT and CRRA, Association between Age and BMI without Control for Selection

5.9.2: Optimism and Pessimism

We report estimates of the RDU model with the flexible Prelec function in Table 5.6. The estimated probability weighting functions for men and women across the two weight groups are displayed in Figure 5.1, and we find some variation in subjective probability weighting.[69] We observe that men with healthy weight are optimistic in their subjective transformation of probabilities, whereas overweight men and women with healthy weight are pessimistic with convex probability weighting functions. Overweight women have an inverse S-shaped probability weighting function, with a concave section for small probabilities and a convex section for high probabilities. Although the figures point to substantial variation in subjective probability weighting we do not find a significant association with BMI for men or women. The marginal effect of BMI on the η (ϕ) parameter has a *p*-value of 0.102 (0.554) for men, and the joint effect of BMI on the η and ϕ parameters is not significant with a *p*-value of 0.260. The story is the same for women, although the probability weighting functions are different from their male counterparts. The marginal effect of BMI on the η (ϕ) parameter has a *p*-value of 0.181 (0.084) for women, and the joint effect of BMI on the η and ϕ parameters is not significant with a *p*-value of 0.205. However, we do find a significant difference in subjective probability weighting between overweight men and women, with women being significantly more optimistic over small probabilities compared to men.[70]

[69] Since we only have two outcomes in each lottery the probability weight is identical to the decision weight for the best outcome, and the decision weight for the worst outcome is one minus that decision weight.
[70] The marginal effect of sex for respondents in the overweight group on the η (ϕ) parameter has a *p*-value of 0.112 (0.005), and the joint effect of sex in the overweight group on the η and ϕ parameters is significant with a *p*-value of 0.017. We do not find a significant association between sex and risk attitudes in the healthy weight group.

	Estimate	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
			Panel A: Main Equations		
r:					
Male overweight	0.267	0.149	0.072	-0.024	0.558
Male healthy weight	0.550	0.133	0.000	0.290	0.809
Female overweight	0.505	0.159	0.002	0.193	0.818
Female healthy weight	0.497	0.123	0.000	0.257	0.738
eta:					
Male overweight	1.300	0.270	0.000	0.771	1.829
Male healthy weight	0.795	0.225	0.000	0.354	1.235
Female overweight	0.763	0.259	0.003	0.255	1.271
Female healthy weight	1.233	0.390	0.002	0.469	1.996
phi:					
Male overweight	1.035	0.140	0.000	0.760	1.309
Male healthy weight	0.907	0.171	0.000	0.572	1.242
Female overweight	0.533	0.122	0.000	0.294	0.772
Female healthy weight	0.873	0.182	0.000	0.516	1.231
mu:					
Male overweight	0.701	0.104	0.000	0.498	0.905
Male healthy weight	0.494	0.078	0.000	0.341	0.647
Female overweight	0.469	0.101	0.000	0.271	0.668
Female healthy weight	0.697	0.109	0.000	0.482	0.911
ρ_{RA}	-0.280	0.340	0.411	-0.946	0.387
			Panel B. Selection Equation		
Constant	-0.197	0.337	0.558	-0.858	0.464
Female	0.122	0.176	0.488	-0.223	0.468
Older	0.530	0.195	0.007	0.147	0.913
Single	-0.008	0.243	0.974	-0.484	0.468
Kids	-0.103	0.219	0.638	-0.533	0.327
Owner	0.499	0.232	0.032	0.043	0.954
Skilled	-0.085	0.229	0.711	-0.534	0.364
Longed	-0.282	0.246	0.253	-0.765	0.201
IncLow	-0.145	0.222	0.512	-0.580	0.290
IncHigh	0.236	0.232	0.309	-0.218	0.691
Region_2	-0.250	0.265	0.345	-0.770	0.270
Region_3	-0.139	0.242	0.567	-0.613	0.336

Table 5.6: RDU with Prelec Weighting Function, Association between Sex and BMI

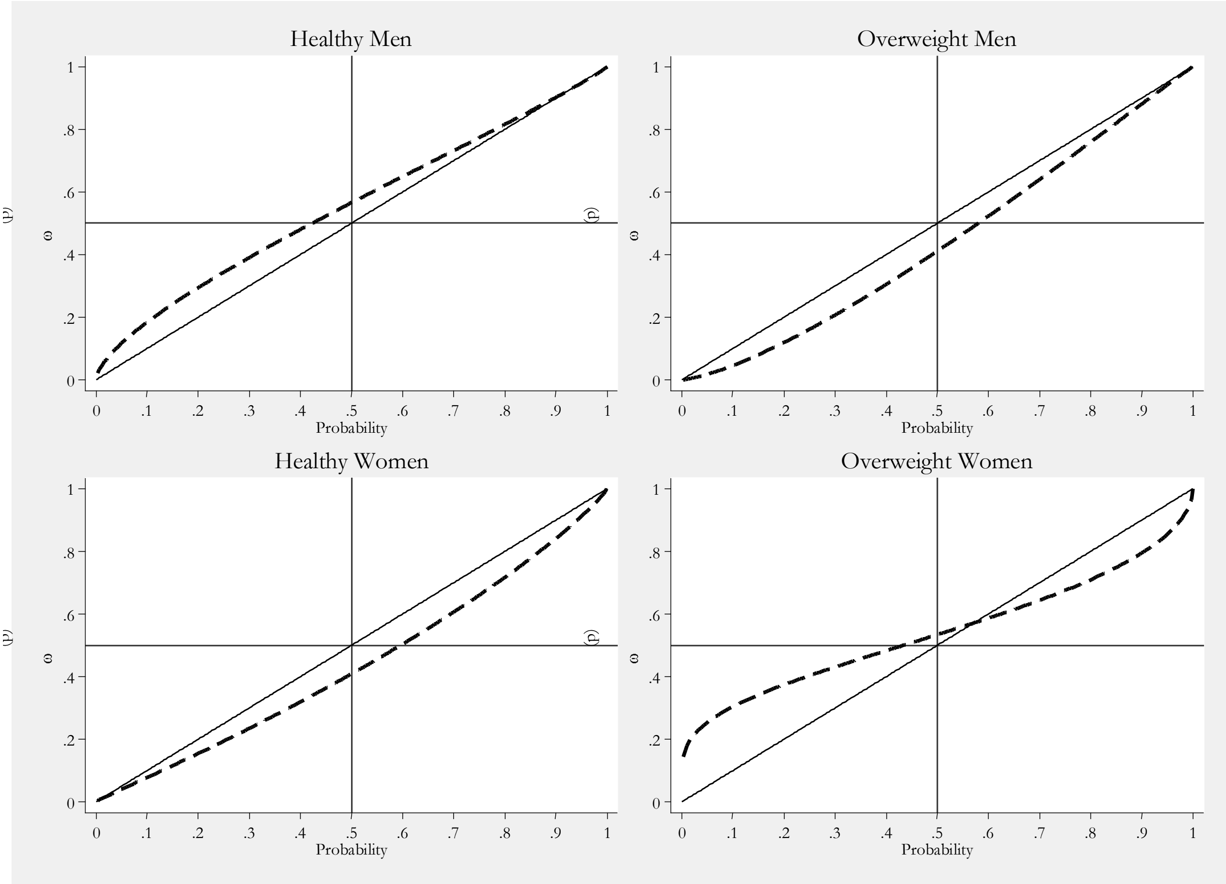


Figure 5.1: RDU with Prelec Weighting Function, Association between Sex and BMI

Given the responses in the individual decision tasks, with greater probability pessimism (optimism) there is smaller (greater) aversion to variability of outcomes, and we observe a decrease in the concavity of the utility function for overweight men and an increase in the concavity for men with healthy weight compared to the estimated parameter values in the EUT model. The estimated CRRA coefficient is 0.27 and 0.55 for overweight and healthy weight men, respectively, and this difference of 0.28 is not statistically significant (*p*-value of 0.154). We also fail to reject the hypothesis that overweight and healthy weight women have identical CRRA coefficients (*p*-value of 0.969).

Looking at the interaction between age and BMI in Table 5.7, we find that the probability weighting function is convex. The only exception is the healthy group of subjects over 40 years of age; this group has a linear weighting function. We do not find any significant differences in the subjective probability weighting functions across the four age and weight groups. However, we do find a significant association between BMI and estimated CRRA for subjects older than 40 years of age: the estimated difference of 0.285 in CRRA between the two BMI categories is significant and has a *p*-value of 0.040. We also find a significant age effect among overweight subjects: the estimated difference of 0.280 in CRRA between the two age groups is significant and has a *p*-value of 0.041.

	Estimate	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
			Panel A: Main Equations		
r:					
Younger overweight	0.625	0.091	0.000	0.446	0.805
Younger healthy weight	0.456	0.126	0.000	0.209	0.703
Older overweight	0.345	0.115	0.003	0.118	0.571
Older healthy weight	0.630	0.097	0.000	0.440	0.819
eta:					
Younger overweight	1.408	0.297	0.000	0.826	1.990
Younger healthy weight	1.819	0.470	0.000	0.898	2.739
Older overweight	1.299	0.292	0.000	0.727	1.871
Older healthy weight	1.020	0.223	0.000	0.583	1.457
phi:					
Younger overweight	1.162	0.288	0.000	0.598	1.727
Younger healthy weight	1.028	0.173	0.000	0.690	1.366
Older overweight	0.890	0.131	0.000	0.633	1.147
Older healthy weight	0.917	0.151	0.000	0.621	1.213
mu:					
Younger overweight	0.442	0.080	0.000	0.286	0.598
Younger healthy weight	0.626	0.096	0.000	0.438	0.814
Older overweight	0.723	0.093	0.000	0.540	0.906
Older healthy weight	0.675	0.094	0.000	0.492	0.859
ρ_{RA}	0.125	0.338	0.712	-0.537	0.786
			Panel B. Selection Equation		
Constant	-0.211	0.340	0.536	-0.878	0.457
Female	0.123	0.180	0.494	-0.229	0.475
Older	0.520	0.196	0.008	0.135	0.904
Single	0.014	0.246	0.954	-0.467	0.496
Kids	-0.100	0.221	0.649	-0.533	0.332
Owner	0.523	0.225	0.020	0.081	0.964
Skilled	-0.068	0.230	0.767	-0.520	0.383
Longed	-0.266	0.248	0.285	-0.753	0.221
IncLow	-0.148	0.223	0.507	-0.584	0.289
IncHigh	0.244	0.233	0.296	-0.213	0.701
Region_2	-0.277	0.268	0.301	-0.801	0.247
Region_3	-0.156	0.244	0.524	-0.635	0.323

Table 5.7: RDU with Prelec Weighting Function, Association between Age and BMI

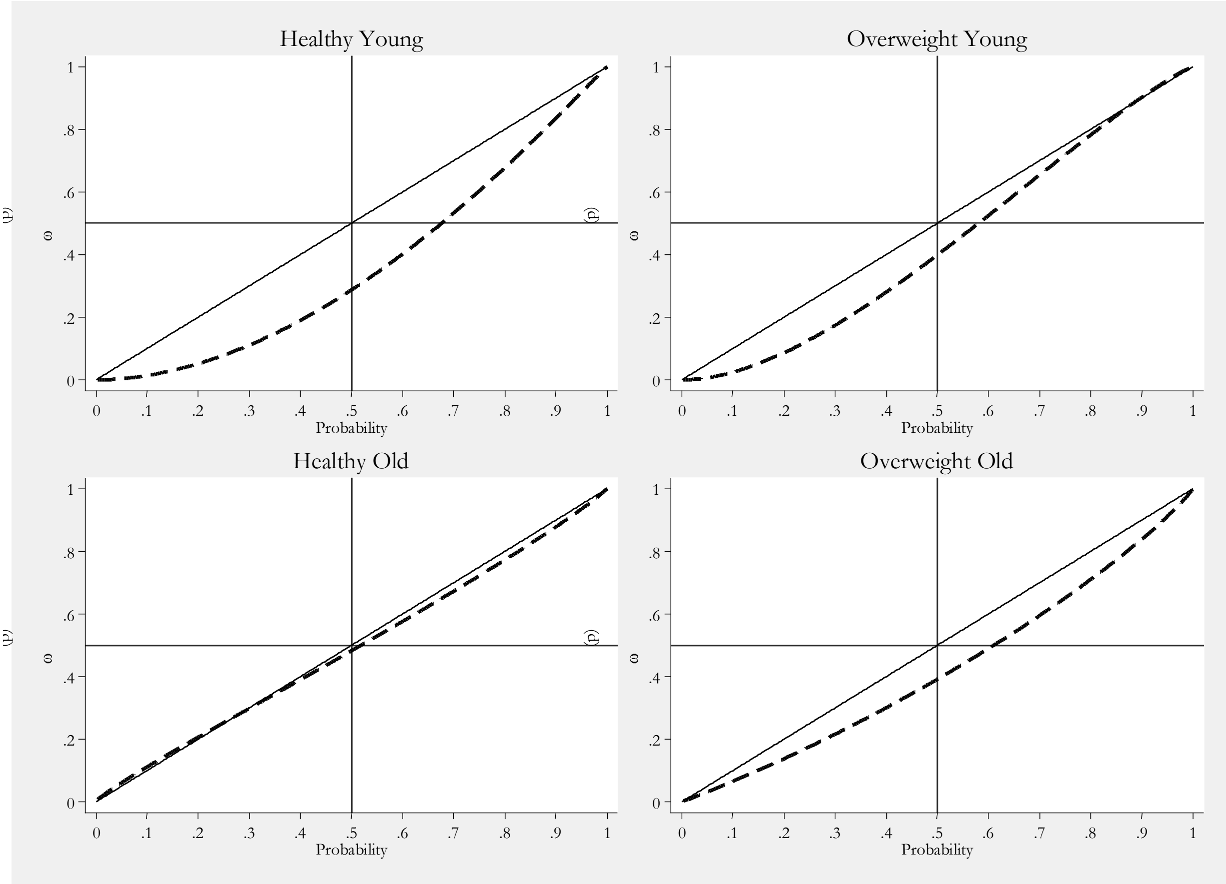


Figure 5.2: RDU with Prelec Weighting Function, Association between Age and BMI

Table 5.8 and Table 5.9 report estimated CRRA coefficients for the two RDU models with no controls for selection. The results in Table 5.8 confirm our previous findings: we do not find a significant association between probability weighting and BMI for men or women, and there is no significant effect of BMI on estimated CRRA for men or women.

	Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
r:					
Male overweight	0.326	0.107	0.002	0.115	0.536
Male healthy weight	0.559	0.126	0.000	0.311	0.807
Female overweight	0.496	0.172	0.004	0.158	0.834
Female healthy weight	0.541	0.091	0.000	0.362	0.719
eta:					
Male overweight	1.395	0.222	0.000	0.961	1.830
Male healthy weight	0.893	0.208	0.000	0.486	1.300
Female overweight	0.869	0.287	0.002	0.306	1.432
Female healthy weight	1.412	0.260	0.000	0.902	1.923
phi:					
Male overweight	1.046	0.133	0.000	0.787	1.307
Male healthy weight	0.938	0.173	0.000	0.598	1.277
Female overweight	0.570	0.138	0.000	0.299	0.840
Female healthy weight	0.914	0.152	0.000	0.616	1.211
mu:					
Male overweight	0.692	0.081	0.000	0.534	0.851
Male healthy weight	0.521	0.071	0.000	0.381	0.661
Female overweight	0.509	0.112	0.000	0.288	0.729
Female healthy weight	0.720	0.083	0.000	0.558	0.882

Table 5.8: RDU with Prelec Weighting Function, Association between Sex and BMI without Control for Selection

	Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
			Panel A: Main Equations		
r:					
Younger overweight	0.616	0.087	0.000	0.446	0.786
Younger healthy weight	0.423	0.116	0.000	0.195	0.652
Older overweight	0.328	0.115	0.004	0.103	0.554
Older healthy weight	0.621	0.094	0.000	0.437	0.805
eta:					
Younger overweight	1.337	0.225	0.000	0.896	1.778
Younger healthy weight	1.770	0.460	0.000	0.869	2.672
Older overweight	1.242	0.256	0.000	0.740	1.745
Older healthy weight	0.968	0.181	0.000	0.614	1.322
phi:					
Younger overweight	1.160	0.290	0.000	0.592	1.729
Younger healthy weight	1.037	0.182	0.000	0.681	1.393
Older overweight	0.873	0.132	0.000	0.615	1.132
Older healthy weight	0.905	0.147	0.000	0.616	1.194
mu:					
Younger overweight	0.430	0.070	0.000	0.292	0.567
Younger healthy weight	0.626	0.106	0.000	0.418	0.834
Older overweight	0.709	0.095	0.000	0.523	0.895
Older healthy weight	0.655	0.077	0.000	0.503	0.806

Table 5.9: RDU with Prelec Weighting Function, Association between Age and BMI without Control for Selection

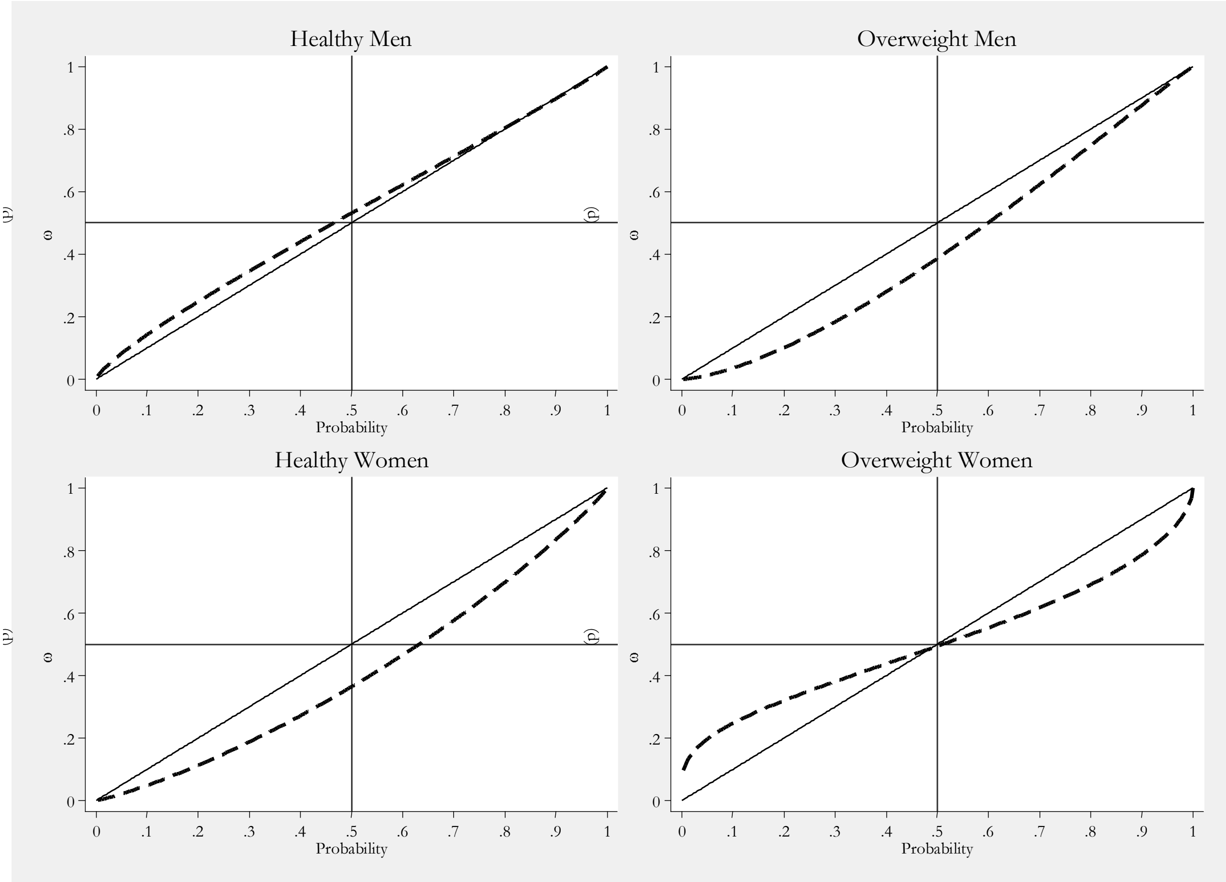


Figure 5.3: RDU with Prelec Weighting Function, Association between Sex and BMI without Control for Selection

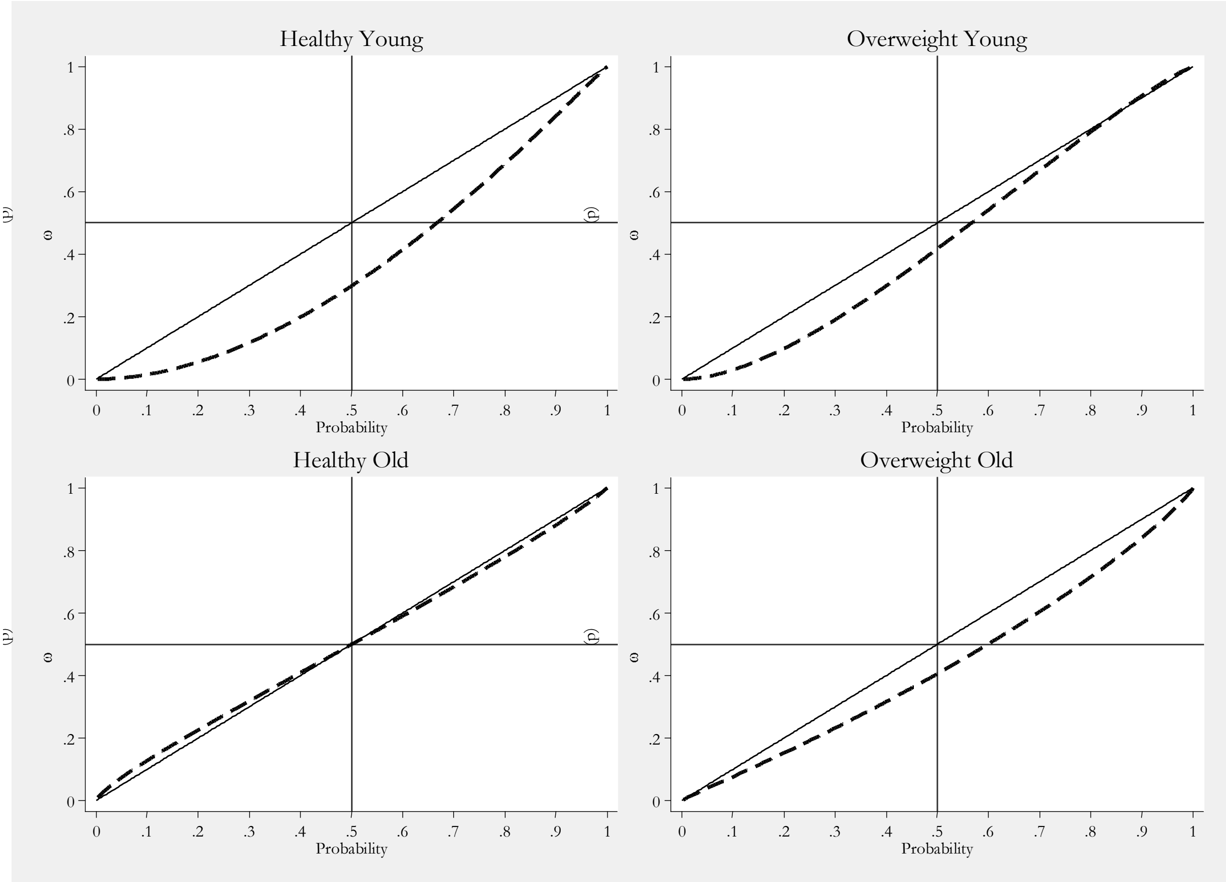


Figure 5.4: RDU with Prelec Weighting Function, Association between Age and BMI without Control for Selection

Figure 5.3 displays the estimated probability weighting functions for men and women, which are similar to those displayed in Figure 5.1. Healthy men have an almost linear probability weighting function, overweight men and healthy weight women have convex probability functions, and overweight women have an inverse S-shaped curve with a concave lower segment and a convex upper segment. The results in Table 5.9 and Figure 5.5 confirm the findings in Table 5.7 and Figure 5.2. There is no significant effect of BMI on probability weighting, but we do find that overweight subjects are significantly less risk averse than healthy weight subjects in the older age group (*p*-value of 0.049).

5.9.3: Discount Rates

Turning to individual discount rates, Table 5.10 shows estimated parameter values from an exponential discounting model assuming RDU with the flexible two-parameter Prelec probability weighting function. We control for the curvature of the utility function and jointly estimate risk aversion and discount rates, as theory requires.[71]

[71] An important maintained assumption in our empirical model is that the risk parameter *r* is constant over time and planning horizons. Thus we assume that the same *r* applies to utility over outcomes in the risk aversion and discount rate tasks, and independently of when the monetary reward is being paid out. This assumption is plausible from both a theoretical and empirical perspective. Andersen, Harrison, Lau and Rutström [2008b] use data from a longitudinal experiment with similar monetary incentives and found some variation in risk attitudes over time, but they did not detect a general tendency for risk aversion to increase or decrease over a 17-month time span from June 2003 to November 2004.

	Estimate	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
delta:					
Male overweight	0.202	0.055	0.000	0.094	0.310
Male healthy weight	0.133	0.045	0.003	0.045	0.221
Female overweight	0.124	0.051	0.015	0.024	0.223
Female healthy weight	0.143	0.039	0.000	0.068	0.219
r:					
Male overweight	0.268	0.148	0.071	-0.023	0.559
Male healthy weight	0.550	0.132	0.000	0.290	0.809
Female overweight	0.506	0.159	0.001	0.194	0.818
Female healthy weight	0.498	0.123	0.000	0.257	0.738
eta:					
Male overweight	1.299	0.270	0.000	0.770	1.828
Male healthy weight	0.795	0.224	0.000	0.355	1.234
Female overweight	0.763	0.259	0.003	0.256	1.270
Female healthy weight	1.232	0.389	0.002	0.470	1.995
phi:					
Male overweight	1.035	0.140	0.000	0.760	1.309
Male healthy weight	0.907	0.171	0.000	0.573	1.242
Female overweight	0.533	0.122	0.000	0.294	0.772
Female healthy weight	0.873	0.182	0.000	0.516	1.231
mu_{IDR}:					
Male overweight	0.477	0.102	0.000	0.276	0.677
Male healthy weight	0.336	0.083	0.000	0.173	0.498
Female overweight	0.397	0.105	0.000	0.191	0.603
Female healthy weight	0.371	0.064	0.000	0.247	0.496
mu_{RA}:					
Male overweight	0.701	0.104	0.000	0.498	0.904
Male healthy weight	0.494	0.078	0.000	0.341	0.646
Female overweight	0.469	0.101	0.000	0.272	0.667
Female healthy weight	0.697	0.109	0.000	0.482	0.911
ρ_{IDR}	0.272	0.115	0.018	0.048	0.497
ρ_{RA}	-0.279	0.340	0.411	-0.945	0.387

Table 5.10: Exponential Discounting and RDU, Association between Sex and BMI

We do not find a statistically significant association between BMI and individual discount rates. Overweight men have an estimated annual discount rate of 20.2%, whilst the estimated annual discount rate for healthy weight men is 13.3%. The results suggest that men with healthy weight are more oriented towards future outcomes and willing to wait longer for a certain return than overweight men, but the estimated difference of 6.9 percentage points is not significantly different from zero (*p*-value of 0.323). Overweight women have an estimated discount rate of 12.4%, and the estimated discount rate for healthy weight women is 14.3%. The difference of 1.9 percentage points is, again, not significantly different from zero with a *p*-value of 0.772.[72]

Turning to the interaction between age and BMI in Table 5.11 we find that younger overweight subjects have an estimated discount rate of 6.2%, while the estimated coefficient for young respondents with healthy weight is 14.0%. Although the difference of 7.8 percentage points is relatively large, it is not significantly different from 0 (*p*-value of 0.215). Older overweight subjects have an estimated discount rate of 17.8%, and the estimated discount rate for respondents with healthy weight in the same age group is 10.6%. This difference of 7.2 percentage points is not significantly different from 0 (*p*-value of 0.118). Finally, we do not find a significant effect of age on estimated CRRA, although the older overweight respondents appear to be more impatient than younger respondents in the same weight class (*p*-value of 0.099).

[72] We do not find a significant effect of sex among overweight respondents, the difference of 7.8 percentage points has a *p*-value of 0.736.

	Estimate	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
delta:					
Younger overweight	0.062	0.038	0.102	-0.012	0.137
Younger healthy weight	0.140	0.038	0.000	0.066	0.214
Older overweight	0.178	0.041	0.000	0.098	0.259
Older healthy weight	0.106	0.030	0.000	0.047	0.165
r:					
Younger overweight	0.626	0.092	0.000	0.447	0.805
Younger healthy weight	0.457	0.126	0.000	0.210	0.703
Older overweight	0.345	0.115	0.003	0.119	0.571
Older healthy weight	0.630	0.097	0.000	0.441	0.819
eta:					
Younger overweight	1.408	0.297	0.000	0.827	1.989
Younger healthy weight	1.818	0.470	0.000	0.898	2.739
Older overweight	1.298	0.292	0.000	0.727	1.870
Older healthy weight	1.020	0.223	0.000	0.583	1.457
phi:					
Younger overweight	1.163	0.288	0.000	0.599	1.727
Younger healthy weight	1.028	0.173	0.000	0.690	1.366
Older overweight	0.890	0.131	0.000	0.633	1.147
Older healthy weight	0.917	0.151	0.000	0.621	1.213
mu_{IDR}:					
Younger overweight	0.527	0.152	0.001	0.229	0.825
Younger healthy weight	0.300	0.058	0.000	0.187	0.413
Older overweight	0.402	0.074	0.000	0.258	0.546
Older healthy weight	0.345	0.060	0.000	0.228	0.462
mu_{RA}:					
Younger overweight	0.442	0.080	0.000	0.286	0.598
Younger healthy weight	0.626	0.096	0.000	0.437	0.814
Older overweight	0.723	0.093	0.000	0.540	0.905
Older healthy weight	0.675	0.094	0.000	0.492	0.859
ρ_{IDR}	0.204	0.106	0.053	-0.003	0.411
ρ_{RA}	0.125	0.337	0.710	-0.535	0.786

Table 5.11: Exponential Discounting and RDU, Association between Age and BMI

There is evidence of sample selection bias with respect to individual discount rates, and the estimated correlation coefficient is 0.272 (0.204) when we control for sex (age) with a *p*-value equal to 0.018 (0.053). The positive correlation between selection into the survey component and responses to the discount rate tasks suggests that respondents to the survey questions have lower discount rates and are more patient than those who select to not answer the questions. There is no evidence of sample selection bias with respect to estimated risk attitudes.

Finally, Table 5.12 and Table 5.13 report estimated discount rates with no controls for selection. The correlation coefficient with respect to discount rates in Table 5.10 and Table 5.11 is positive and significantly different from 0, which indicates that the estimated discount rates are higher in the model that controls for selection compared to a similar model that does not control for selection. Table 5.12 shows that the uncorrected estimated discount rates generally are lower than the corrected coefficients in Table 5.10, and we confirm the previous finding that there is no significant association between discount rates and BMI for men or women. The results in Table 5.13 confirm the findings in Table 5.11: we do not find a significant association between discount rates in the young and older age groups, respectively.

	Estimate	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
delta:					
Male overweight	0.144	0.035	0.000	0.075	0.213
Male healthy weight	0.105	0.036	0.003	0.035	0.175
Female overweight	0.100	0.041	0.015	0.020	0.181
Female healthy weight	0.103	0.026	0.000	0.052	0.155
r:					
Male overweight	0.396	0.105	0.000	0.191	0.601
Male healthy weight	0.603	0.117	0.000	0.373	0.832
Female overweight	0.549	0.143	0.000	0.269	0.828
Female healthy weight	0.589	0.092	0.000	0.409	0.769
eta:					
Male overweight	1.260	0.215	0.000	0.838	1.682
Male healthy weight	0.835	0.184	0.000	0.473	1.196
Female overweight	0.799	0.216	0.000	0.375	1.222
Female healthy weight	1.299	0.250	0.000	0.809	1.790
phi:					
Male overweight	1.039	0.138	0.000	0.768	1.309
Male healthy weight	0.936	0.170	0.000	0.602	1.270
Female overweight	0.557	0.116	0.000	0.329	0.784
Female healthy weight	0.901	0.153	0.000	0.601	1.201
mu_{IDR}:					
Male overweight	0.414	0.077	0.000	0.264	0.564
Male healthy weight	0.317	0.077	0.000	0.167	0.467
Female overweight	0.376	0.096	0.000	0.188	0.563
Female healthy weight	0.336	0.050	0.000	0.237	0.434
mu_{RA}:					
Male overweight	0.664	0.081	0.000	0.505	0.822
Male healthy weight	0.504	0.064	0.000	0.380	0.629
Female overweight	0.484	0.081	0.000	0.325	0.643
Female healthy weight	0.700	0.084	0.000	0.535	0.865

Table 5.12: Exponential Discounting and RDU, Association between Sex and BMI without Control for Selection

	Estimate	Standard Error	*p*-value	Lower 95% CI	Upper 95% CI
delta:					
Younger overweight	0.036	0.035	0.303	-0.033	0.105
Younger healthy weight	0.119	0.034	0.000	0.054	0.185
Older overweight	0.145	0.034	0.000	0.077	0.212
Older healthy weight	0.094	0.028	0.001	0.040	0.148
r:					
Younger overweight	0.699	0.127	0.000	0.449	0.949
Younger healthy weight	0.484	0.121	0.000	0.247	0.721
Older overweight	0.422	0.106	0.000	0.214	0.630
Older healthy weight	0.648	0.092	0.000	0.467	0.829
eta:					
Younger overweight	1.224	0.206	0.000	0.827	1.621
Younger healthy weight	1.645	0.470	0.000	0.723	2.567
Older overweight	1.059	0.214	0.000	0.639	1.480
Older healthy weight	0.924	0.171	0.000	0.590	1.259
phi:					
Younger overweight	1.121	0.297	0.000	0.629	1.793
Younger healthy weight	1.049	0.196	0.000	0.666	1.432
Older overweight	0.826	0.126	0.000	0.579	1.073
Older healthy weight	0.901	0.146	0.000	0.616	1.187
mu_{IDR}:					
Younger overweight	0.475	0.160	0.003	0.162	0.788
Younger healthy weight	0.289	0.053	0.000	0.185	0.393
Older overweight	0.370	0.065	0.000	0.243	0.497
Older healthy weight	0.338	0.058	0.000	0.225	0.452
mu_{RA}:					
Younger overweight	0.415	0.069	0.000	0.249	0.550
Younger healthy weight	0.614	0.113	0.000	0.392	0.836
Older overweight	0.648	0.085	0.000	0.481	0.789
Older healthy weight	0.642	0.075	0.000	0.495	0.815

Table 5.13: Exponential Discounting and RDU, Association between Age and BMI without Control for Selection

5.10: Conclusion

We elicit individual risk attitudes and discount rates from the general adult population in Denmark and investigate how these latent preferences are associated with body mass. The results do not point to a significant association between relative risk aversion and body mass for men and women. However, we do find a significant effect of BMI on relative risk aversion for subjects older than 40 years of age, with overweight subjects being significantly less risk averse than subjects with healthy weight. The results do not point to a significant association between probability weighting and BMI. Moreover, we do not find a significant correlation between individual discount rates and BMI. We estimate individual discount rates using the exponential discount function, and the experimental design does not allow us to estimate alternative functional forms with a constant risk premium to delayed outcomes, such as quasi-hyperbolic models. This is an important extension to investigate the association between time inconsistent decision making and BMI, and health related behavior more generally.[73]

5.10.1: Strengths of the research

The strengths of our research are discussed throughout the chapter. To summarise:

- We utilise elicitation methods designed specifically for the assessment of risk and time preference.
- We use real monetary payments providing robustness to our estimates.
- We jointly estimate risk and time preference eliminating the bias resulting from assumptions of risk neutrality.

[73] Harrison, Lau and Rutström (2010) use a finite mixture model to evaluate the correlation between smoking and time inconsistent behavior. Finite mixture models require relatively large samples to estimate the fraction of choices that can be represented by several latent preference structures, and our sample is unfortunately not large enough to evaluate these types of models.

- We control for sample selection reducing the potential bias from non-randomly selected samples.
- We extend our model to allow for the RDU model with non-linear utility and probability weighting, better reflecting a multi-criteria approach to decision making.
- We allow for behavioural error by introducing a structural noise parameter which allows the error the standard deviation of the error term to differ from 1, which essentially controls for heteroscedasticity.

5.10.2: Limitations

As with any research there are limitations to our approach. In this section we outline each identified limitations, discuss reasons, potential consequences and provide direction for further research.

Sample Size

A key criticism of our work is the seemingly small sample size (n=154). There are two key causes of the small sample size; (1) the cost of experimentation and (2) the selection into the follow-up survey. As stated, real monetary payment were utilised within the experiment with average pay-out per participant exceeding £100. Researchers utilising these elicitation methods, therefore, face a choice between real monetary payments and smaller sample sizes or hypothetic payments and larger sample sizes. The clear preference for real monetary payment has previously been discussed and its importance outweighs the concerns of smaller sample size. The second cause of the sample size is limited selection into the follow-up survey (n=253 in the main experiments to n=154 returning the follow up survey). Whilst the original sample is representative of the Danish population, the key concern is, therefore, whether the sub-sample is also. As we control for sample selection we are able to identify observable variables which exhibit a significant relationship with selection into the follow up survey and find that older individuals and those who are home owners are more likely to select into the survey. This limitation is acknowledged and reflected in discussions. A consequence of the smaller sample size is an inability to further research through, for example, a three-way interaction between BMI, age and gender. Whilst econometrically possible, it is not advisable due to the resulting eight sub-groups which would bring the size of the each group below 20 participants. Whilst sample size is acknowledged as a limitation, it is worth reflecting in the context of the existing literature. Six studies, of either risk or time preference, are identified and are presented in Section 5.5. Our sample size is reflective of experiments conducted in this field of research with only two of the six exhibiting a large sample size.

Delay between measure of risk and time preference and weight status

A further criticism is the two year delay between the elicitation of risk and time preferences and the collection of data concerned with weight status. The delay is not, however, an issue if two assumptions are satisfied; (1) the stability of risk and time preferences and (2) the stability of weight, over the two year period. Regarding the stability of risk and time preferences, support for this has been provided in Section 5.7.3. Andersen, Harrison, Lau and Rutström (2008) examine the temporal stability of risk attitudes and time preferences in the Danish population over a 17 month period and observe relative stability. Regarding the stability of weight, longitudinal studies of weight show very limited changes in BMI. A large study (n=18,975) conducted over a 15 year period in Finland found, on average, BMI increased by 0.4 in men and 0.3 in women and a further large study (n=5,622) conducted over a 17 year period in Sweden found, on average, BMI increased by 1.4 in men and 1.0 in women (Lahti-Koski et al., 2007 and Berg et al., 2005, respectively). These findings evidence a relative stability in BMI over time in the two Nordic countries studied and as the delay between measurements in our study is only over a two year period (in comparison to the studies presented) there is a high level of confidence in accuracy. Further, it is argued that due to the lack of current evidence regarding risk and time preferences and BMI, the utilisation of an opportunity to contribute to the evidence far outweighs the potential limitations presented by the delay.

The comparability of choices made over financial and health decision

An assumption of our approach is that risk and time preferences elicited from financial decision making transfers to the domain of health decisions. A key cause of the use of financial decisions to the elicit preference is the relative difficulty in designing elicitation tasks that draw out preferences directly from health choices and specifically choices in the domain of obesity. Galizzi, Miraldo and Stavropoulou (2016) present six methods by which to measure risk aversion in health. Four of the six approaches seek to elicit risk preferences from health specific methods. Three of these methods are hypothetical, self-reported measures of risky behaviour rather than a direct measure of risky choices by which to elicit preferences (Galizzi, Miraldo and Stavropoulou, 2016). The fourth approach uses the value of the certainty equivalent (i.e. the smallest amount of dollars or relapse free days that respondent would be willing to accept instead of the lottery presented) as a proxy for risk preference (Galizzi, Miraldo and Stavropoulou, 2016). Galizzi, Miraldo and Stavropoulou (2016) propose an alternative method that adapts the paired lottery questions (as utilised in our study) to the health domain. For researchers, the choice is, therefore, between an elicitation method consisting of hypothetical choices in the health domain or an elicitation method consisting of real monetary decisions but outside of the health domain. Within our discussion we present a clear argument and preference for non-hypothetical approaches.

Quasi hyperbolic/Hyperbolic discounting

A further limitation of the study is that we do not explore quasi-hyperbolic or hyperbolic discounting functions. This limitation is due to the experimental design of the original elicitation tasks where the earliest payment was made after one month, therefore, not capturing preferences made with the prospect of immediate payoff. In Chapter 2 we outline the theoretical importance of immediate gratification and consumption choice and, therefore, an important extension to investigate the association between time inconsistent decision making and BMI, and health related behavior more generally.

Self-reported BMI

The limitation of working with self-reported BMI has been discussed previously in Chapter 1. We utilised self-reported BMI in this study as collection of objectively measured BMI was not feasible. Due to little consistency of the measurement error resulting from self-reported BMI a robust correction method does not exist and researchers are best to use self-reported BMI as it is reported rather than risk additional bias by attempting to correct for possible error (see, Nyholm et al. (2007), Spencer et al. (2002) and Faeh and Bopp [2009]). This is the approach we adopt whilst acknowledging the limitation of this decision.

5.10.3: Summary of findings

We elicit individual risk attitudes and discount rates from the general adult population in Denmark and investigate how these latent preferences are associated with body mass. The results do not point to a significant association between relative risk aversion and body mass for men and women. However, we do find a significant effect of BMI on relative risk aversion for subjects older than 40 years of age, with overweight subjects being significantly less risk averse than subjects with healthy weight. The results do not point to a significant association between probability weighting and BMI. Moreover, we do not find a significant correlation between individual discount rates and BMI.

Firstly reflecting on the insignificant findings, a key question is why we do not observe evidence for the proposed hypotheses? Broadly this is for one of two reasons. Firstly, a relationship between time and risk preferences and BMI may simply not exist and, therefore, we do not detect an effect. Secondly, an effect may not be detected due to a limitation of our approach. These limitations are outlined above and we discuss the justifications for the approach taken and, therefore, why we are confident in our conclusions. We do, however, acknowledge these limitations and would indeed suggest caution in the broad generalizability of these findings. In addition we suggest valuable further research to complement our contribution to the literature. These are outlined below in Section 5.10.4.

Secondly we reflect further on the significant finding of the association between risk preference and BMI in older adults. Few previous studies have examined preferences within subgroups of the population with no previous studies examining age differences. Previous studies have found a significant gender effect. Specifically, Galizzi and Miraldo (2012) and Koritzky, Yechiam, Bukay and Milman (2012) both find evidence that overweight men are significantly less risk averse than their healthy weight counterparts. Whilst both studies collect information on age, neither investigates an interaction between age and risk preferences. Broadly, there is some evidence for a relationship between age and risk aversion which suggests that risk aversion increases slowly between child and adulthood (Paulsen et al., 2012, Levin and Hart, 2003, Levin et al., 2007, Rakow and Rahim, 2010 and Weller et al., 2010). In the domain of obesity research it is suggested that the salience of risk from overweight and obesity may increase with age as, for example, individuals are exposed to greater incidence of comorbidities either within themselves or within their social groups. The risk of diabetes, for example, increases with age, with individuals over the age of 40 at particularly heightened risk (NHS, 2016). Within our research we define older adults as those over 40-years-old. It can be hypothesised, therefore, that we do not observe a difference in risk attitudes between younger healthy weight and younger overweight individuals due to younger adults in general lacking the perception of obesity as a risky behaviour i.e. an young individual may be risk averse but does not consider obesogenic behaviour as risky and, thus, behaves in a similar manner to individuals who are less risk averse. Conversely, among older adults as the salience of poor health outcome increases, those who are risk averse begin to maintain a healthy weight whilst less risk averse are more likely to be overweight or obese.

So what can we learn from these findings? We find some evidence that overweight individuals are less risk averse. With regards to the presented hypothesis, our research evidences an observable variable which may lead to inequalities in obesity and related co-morbidities particularly in older adulthood where risk of the development of related comorbidities is heightened. Further, as with the findings of Chapter 4, we provide empirical evidence of differing risk preferences which can be built into economic models to better select policy options and better predict behavioural responses to such interventions. In particular we provide the foundation for the opportunity to understand the potential differing behavioural responses of individuals with varying levels of risk aversion and, thus, an opportunity to ensure policies are not widening health inequalities. A specific area of interest is policies involving risk communications of obesity. Risk communication aims to increase awareness of risk, influence behaviour change and encourage informed participation in decision-making about risk issues (Rohrmann, 2008). Risk communication represents a significant investment by governments in the effort to tackle obesity and, thus, for effective risk communication, a sound understanding of risk perceptions and attitudes is indispensable.

5.10.4: Reflections on wider and future research

Here we reflect on the relationship between time and risk preferences and other behaviours with potentially negative health outcomes. The earliest research to empirically test experimentally elicited preferences with individual health related behaviours is Fuchs (1982) and finds more future-orientated individuals were more likely to engage in health promoting behaviours, for example physical activity, and less likely to engage in behaviours associated with negative health consequences, such as smoking (Fuchs, 1982). Experimentally elicited measures of risk and time preference have also been use to explore health related behaviours such as smoking (Sutter et al., 2013; Harrison, Lau and Rutström 2010; Chabris et al. 2008; Anderson and Mellor 2008; Barsky et al. 1997; Viscusi and Hersch, 2001), drinking (Sutter et al. (2013); Anderson and Mellor 2008; Barsky et al. 1997), drug abuse (Kirby and Petry 2010), seat belt usage (Anderson and Mellor 2008), demand for medical screening tests (Picone et al. 2004), vaccines (Chapman and Coups 1999) and risky sexual behaviour (Chesson et al., 2006 and Lammers and van Wijnbergen, 2007). All papers outlined find some effect of time and risk preference on the various health related behaviours, however, findings are not consistent in significance or magnitude across studies. A few of these studies comment of the relationship between age and preferences generally (Barsky et al., 1997, Kirby and Petry, 2004, Sutter et al., 2013 and Chesson et al., 2006), however, with the exception of Harrison, Lau and Rutström (2010), none of the studies explore interactions between sociodemographic variables and the health related behaviour of interest. Harrison, Lau and Rutström (2010) find that male smokers have significantly higher discount rates than male non-smokers, however, no significant association was found among women. The authors do not, however, explore an interaction between age and discount rates or risk preferences. We have previously highlighted the hypothesised relationship between risk preferences, age and BMI and, in the context of previous research, further highlights the contribution our research to the wider literature.

Chapter 6 discusses the direction of future research more broadly and so here we outline some key ideas drawn from discussions presented in this section. Firstly, to understand the intricacies of individual risk preferences and weight status future research should consider experimentation with large sample sizes. In particular, an ability to elicit sufficient risk preference to support the exploration of multiple weight status (for example, healthy weight, overweight and obese). The research we present provides evidences for further research and should be used as justification for further funding. Further future studies should incorporate the ability to provide payments in the immediacy to allow for examination of hyperbolic discounting. Finally, experimentation methods could be extended to contain lotteries which include a probability of losing money. Whilst, it may prove problematic to gain ethical approval for experimentation whereby individuals lose their own money, one could set up experiments whereby the first task results in payment which is actively given to participants followed by secondary task which include a probability to lose earning from the first task.

Chapter 6

Discussions

6.1 Overview of the thesis

This thesis presents four studies which explore factors associated with weight status, weight loss and attrition. Whilst each of the chapters can be read individually, the findings from each build upon one another to provide the reader with a more comprehensive understanding of the subject matter.

The first study, presented in Chapter 2, explores thirty-one factors[74] associated with weight loss resulting from a weight management programme. We present the observed relationships between each of the thirty-one factors and the three weight loss outcomes (percentage weight change, BMI change and significant weight loss) in the context of the theoretical and empirical literature. The majority of individuals observed lose weight during the programme, however, the extent of weight loss success is conditional on several observable factors. In summary, as a standalone chapter, our research contributes to the existing knowledge as follows:

- We utilise a larger sample size than any of the existing empirical literature exploring predictors of weight loss.
- The service studied is one of the largest providers of weight management services in UK and worldwide and, thus, the potential impact of our research is substantial as findings are generalizable to a much larger audience.

[74] Age, gender, ethnicity, deprivation decile, has a partner, has children, employment status, level of education, perception of local area, initial BMI, initial weight loss, referral type, time between stages of the programme, consistency of attendance, smoking status alcohol consumption, perception of diet, energy expenditure, disability status, presence of CVD, mobility conditions, diabetes, hypertension, depression, stress and personality scores.

- We explore a richer and more comprehensive set of variables than any of the existing empirical studies of predictors of weight loss.
- We also contribute new knowledge in the form of the variables explored. Specifically, perception of local area, physical health, smoking, time between stages of the programme, self-referral, consistent attendance and the presence of children.

As is common in the existing empirical literature, the findings from this chapter are conditional on individual's participation into the latter stages of the programme where weight outcomes are measured. In other words, our sample is limited to those who attend weeks ten and twelve of the programme. Whilst comparable to existing empirical studies we acknowledge potential bias in the results of Chapter 1. The potential bias may take one of two forms. Firstly selection into the latter stages of the programme may be conditional on observable variables. Secondly, selection into the latter stages of the programme may be conditional on unobserved variables which affect both engagement and weight loss. We, therefore, present two further chapters to explore and correct for these potential biases.

The first of these two chapters, presented in Chapter 3, utilises the thirty-one variables outlined in Chapter 2 to explore attrition from the weight management service. Engagement at week 10 and engagement at week 12 (the final week) of the service comprise the outcomes variables of interest. We present the observed relationships between each of the thirty-one factors and engagement to weeks ten and twelve of the service in the context of the theoretical and empirical literature. Overall several factors are found to exhibit a significant relationship with attrition. This chapter provides evidence that the findings in Chapter 2 may be biased by non-random selection i.e. there are observable variables that predict engagement to the latter stages of the programme. Regarding our contribution to the existing literature, as above, the sample size, the potential impact and the variables explored are all noteworthy features of this chapter. Further, very few existing empirical studies present the findings of both predictors of weight loss and attrition, from a single weight management service, in a single publication. Given the findings of this chapter, it is argued that presentation of both sets of outcomes provides a much richer and more comprehensive understanding of weight management services and, by acknowledging potential biases, begins to suggest where inequalities in outcomes may develop. We discuss this in more detail later in this chapter.

The third study, presented in Chapter 4, utilises statistical methods to correct for non-random sample selection resulting from unobserved variables to re-examine expected weight loss outcomes. As previously stated, the weight loss outcomes presented in Chapter 2 are conditional on individual participation in weeks ten and twelve of the service. The statistical method utilised in Chapter 4 tests for correlation between the error terms of both the sample selection equation (i.e. engagement at week ten or twelve, presented in Chapter 3) and the main equation (i.e. weight loss outcomes, presented in Chapter 2). If found to be correlated it suggests an unobserved variable(s) is significant to both engagement and weight loss outcomes, thus, biasing results of analyses. If correlation is detected the method corrects for this bias. Broadly, corrections can occur in the coefficients of the variables explored in Chapter 2 leading us to differing conclusions from those previously presented or corrections can occur in the constant term. Attrition is a well discussed issue within the literature, yet our research represents the first to utilise selection models in an evaluation of a group based weight management service to correct for unobserved bias. Attrition is, more generally, a problem observed throughout the health system and, therefore, in addition to previously mentioned contributions to the literature, our research in this chapter represents an alternative and more sophisticated statistical method by which to handle attrition.

We evidence a requirement to correct for non-random attrition in analysis of BMI change. Whilst we observe little different in the coefficients of the variables previously explored, we find evidence of an upward shift in the constant term at weeks ten and twelve. In terms of our understanding of the variables of interest, we do not observe any significant changes from our findings in Chapter 1, however, unlike previous empirical studies, acknowledgement and control of potential biases provides a much richer and more comprehensive understanding of weight management services and provides assurance in the conclusions of the research. The observed significant changes in the constant terms do, however, have implications for economics assessments of weight management services. Later in this chapter we reflect on our findings in the context of discussions of effectiveness and cost-effectiveness first introduced in Chapter 1.

Chapter 4 also highlights that, despite the richness of variables included, we find only 21-40% of variability in the data sets is accounted for by the statistical models. As discussed in Chapter 1, there is an identified need to account for theoretically grounded behavioural factors within examinations of obesity and, therefore, to further our understanding we explore two concepts prevalent in the behavioural economics literature but which have rarely been utilised in studies of obesity.

Chapter 5 introduces and explores two key behavioural factors of risk preference and time preference in relation to being overweight or obese. Whilst the theoretical importance of time preference and risk preferences and obesity is prevalent in the existing literature very few empirical examinations are available. In addition, our research advances knowledge by:

- Jointly estimating risk and time preference, eliminating the bias resulting from assumptions of risk neutrality.
- Controlling for sample selection (utilising methods presented in Chapter 4) reducing the potential bias from non-randomly selected samples.
- Extension of existing models to allow for the RDU model a single-criteria model where risk preferences are explained by non-linearity in both utility and probability space.
- Allowing for behavioural error which controls for heteroscedasticity.

Whilst we do not find any significant evidence of a relationship between time preference and BMI, we do find some evidence of an association between risk aversion and being overweight in older adults. We reflect on this finding in the context of results from Chapters 2 to 4 later in this final chapter.

As previously stated, the four research chapters presented in this thesis can be read independently of each other; however, there is greater value in the joint presentation of the findings. Each chapter builds upon the findings of the previous studies to build a rich and comprehensive assessment of variables associated with weight status, weight loss and attrition. Further, throughout the thesis we build an increasingly sophisticated methodological approach to the evaluation of weight status, weight loss and attrition which guides the reader through current approaches and their limitations, the options available for more comprehensive assessments and transparently presents the implications of these various methodological approaches.

6.2 Summary of findings

Before discussing the finding of the four research chapters in more depth we present a brief overview of findings.

Demographics

- We find evidence that older individuals experience better weight loss outcomes as a result of the weight management service. We also find that older individuals with a BMI ≥25 are less risk averse than their healthy weight counterparts.
- We find that more educated individual experience better weight loss outcomes as a result of the weight management service.
- Individuals with children are less likely to attend and we find evidence of lower weight loss compared to individuals without children.

Weight factors

- Although there is some complexity, regarding the key indicator of 'significant weight loss' at both weeks, we find a higher BMI at referral is associated with worse weight loss outcomes.
- On all measures of weight loss and attrition, individuals who experience higher weight loss at week two experience more successful outcomes.

Aspects of the programme

- We find individuals who consistently attend the service experience better weight loss outcomes and are more likely to attend until the latter stages of the programme.
- We find mixed results regarding the number of days between registration and starting the service. We find individuals who take more days to starts are less likely to attend, however, of those that do; they are more likely to experience better weight loss outcomes.
- We find some evidence that individuals who self-refer experience better weight loss outcomes compared to individuals referred for by a health professional.

Health behaviours

- Smokers are less likely to attend compared to non-smokers, however, of those that do they experience better weight loss outcomes.
- We find some evidence that individuals who drink alcohol above recommended levels experience lower weight loss compared to those who drink within guidelines.
- We find some evidence that individuals who perceive their diet to be healthier prior to starting the weight management service experience lower weight loss compared to those who perceive their diet to be unhealthier.

Physical health

- Whilst we find evidence that diabetic individuals are more likely to attend, we also find they experience lower weight loss compared to non-diabetic counterparts.
- We find some evidence that individuals with CVD experience lower weight loss compared to individuals without CVD.

Mental health

- We find evidence that individuals with depression are less likely to attend the service than individuals without a mental health condition.

6.3 Evidence for the effectiveness of the weight management service

In Chapter 1 we present the objectives of weight management services which are as follows:

- Average weight loss among participants is 3%.
- At least 30% of participants lose at least 5% of their initial body weight.
- Are effective at 12 months or beyond.

(NICE, 2014)

Amongst individuals who attended the final week of the service (week 12, n=1,150) we find average percentage weight loss is 6.6%. Further, using observations from all participants (n=2,037) we find 46% of individuals experience ≥5% weight loss during the service. Due to timescales, a limitation of our research is a lack of longer term outcome measures. We do, however, observe weight measurements for 294 individuals, 6 months after commencing the service. For these individuals, average percentage weight loss is 8.9%. It should be noted, however, that this sample represents only 14% of individuals who start the service and may be subject to bias due to non-random selection into this measurement.

Reflecting back to discussions within Chapter 1, a key question is whether the weight management service provides individuals with the capacity to match the complexity of the system. The weight outcomes presented above certainly suggest that the service has provided individuals with the capacity to resist obesogenic factors in the environment, enabling successful weight loss. Further, in a follow up survey to a small non-random sample of individuals who attended the service (n=100), 99% of individuals reported healthy behaviour change as a result of the programme agreeing that the programme provided them with the knowledge to eat more healthily.

As outlined in Section 6.1, we provide further analyses in Chapter 4 in which we control for non-random sample selection resulting from unobserved variables into the latter stages of the service. Reflecting only on percentage weight change analyses, due to the focus of this measurement outcome within NICE guidance (NICE, 2014), we find no significant evidence of bias resulting from unobserved variables effecting both selection and percentage weight loss providing further assurances regarding the conclusions of effectiveness outlined above.

6.4 Inequalities

The above discussions suggest an overall positive impact of the weight management service on obesity. These overall findings are not, however, unique to this thesis, as reported in Table 1.7 in Chapter 1 where we map identified studies to the NICE guidance criteria for behavioural weight management programmes and find the majority, do indeed, meet these overall objectives.

In the context of the efficacy of weight management services two of our primary research questions are; (1) 'what observable factors predict weight loss in a behavioural weight management programme?' and (2) 'what observable factors predict attrition in a behavioural weight management programme?' (Section 1.8, Chapter 1). In Chapter 2 and 3 of this thesis we answer these questions and discuss our findings in the context of previous research. These findings are summarised above. Within the conclusions of Chapter 2 and 3 we acknowledge the implication of our findings on broader discussions of, for example, complex system thinking and health inequalities. In this chapter we present discussions regarding these broader issues.

Reflecting back to discussion of health inequalities we quote the work of Harrison (2013) who posits that "*we care a lot about the 'winners' and 'losers' from policy*". Harrison (2013) proposes that policy based on identifying which interventions demonstrate the most positive average effect may, in fact, result in increasing health inequalities if they do not account for intra-distributional effects. As previously discussed, if the underlying probability distribution is, for example, bimodal, the average effect may look positive, however, the intra-distributional effects may indicate a clear divide between those for whom the intervention is successful and those for whom it is not.

So far we have presented the average effects of the weight management service. Whilst of interest, simply observing the average effect does little to support our understanding, or at least our identification, of inequalities. To further examine the efficacy of the weight management service we, therefore, present Figures 6.1 and 6.2 which plot the frequency of percentage weight loss for those engaged at weeks 10 and 12 (the grey shaded areas) and overlay the normal density distribution (the black curve) to enable comparison between the two. We observe that the frequency plot and the normal density overlay are aligned which suggests that overall we do not observe an obvious divide between the weight outcomes of individuals.

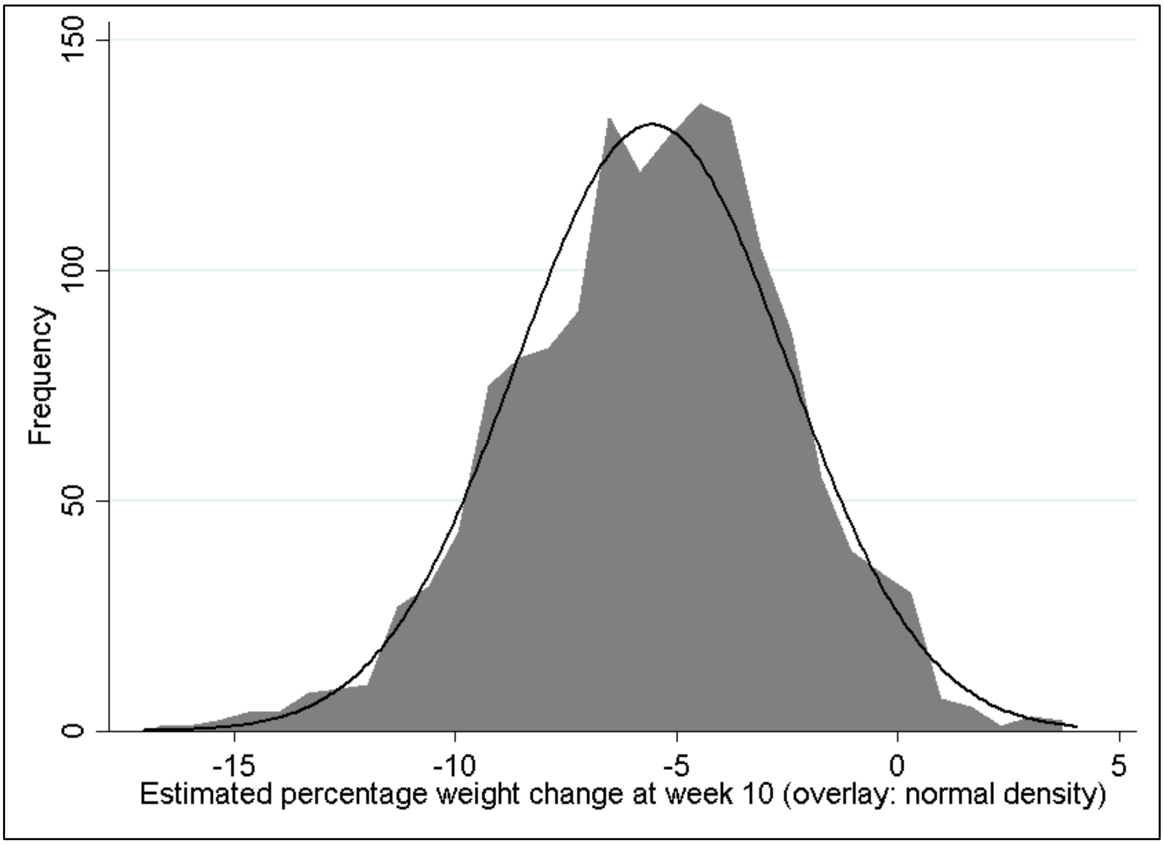


Figure 6.1: Frequency plot of estimated percentage weight change at week 10.

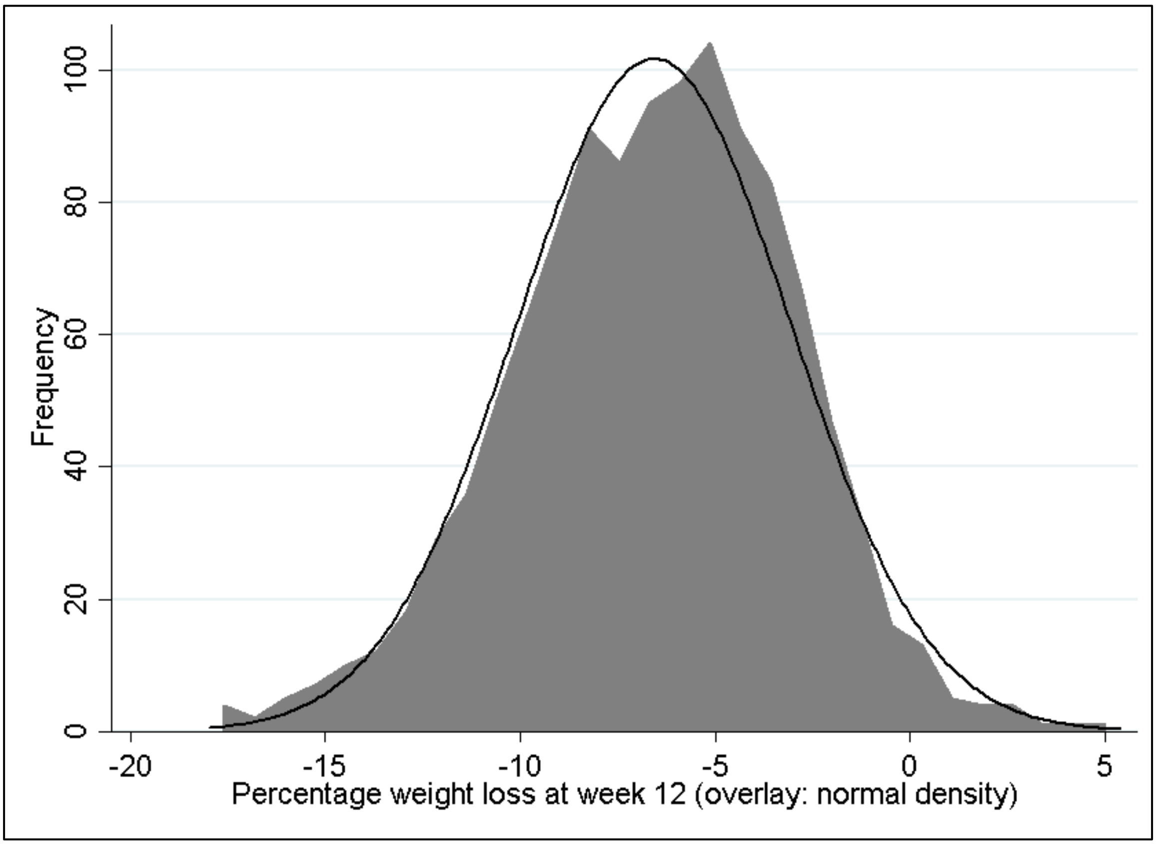


Figure 6.2: Frequency plot of percentage weight change at week 12.

From Figures 6.1 and 6.2 we do not observe distinct groupings of outcomes as the frequency distribution largely following the normal density curve. Some of the strongest predictors of weight loss and attrition from the weight management service do, however, indicate increasing disparities between individuals. Below we discuss two variables; initial weight loss and consistent attendance.

Initial weight loss

The results of analyses in Chapter 2 find initial weight loss (i.e. weight loss at week two of the service) to be a strong predictor of successful outcomes. On all measures of success, i.e. percentage weight change, BMI change, significant weight loss and engagement at the latter stages of the programme, we find initial weight to be a significant predictor of success. Of interest in current discussions is whether the extent of initial weight loss accounts for disparities in overall weight outcomes or whether these disparities increase throughout the service. Figure 6.3 present evidence for the latter. At week two average percentage weight loss is 1.5%. The dark grey line in Figure 6.3 plots the cumulative percentage weight loss for individuals losing more than 1.5% of original body weight at week two. The lighter grey line plots the cumulative percentage weight loss for individuals losing less than 1.5% of original body weight at week two. From the graph we observe an increasing disparity from a difference of 1.5 percentage points in week 3 to a difference of 2.7 percentage points in week 12 i.e. week-on-week individuals whom exhibit above average initial weight loss outperform individuals with below average initial weight loss resulting in increasing disparities over time.

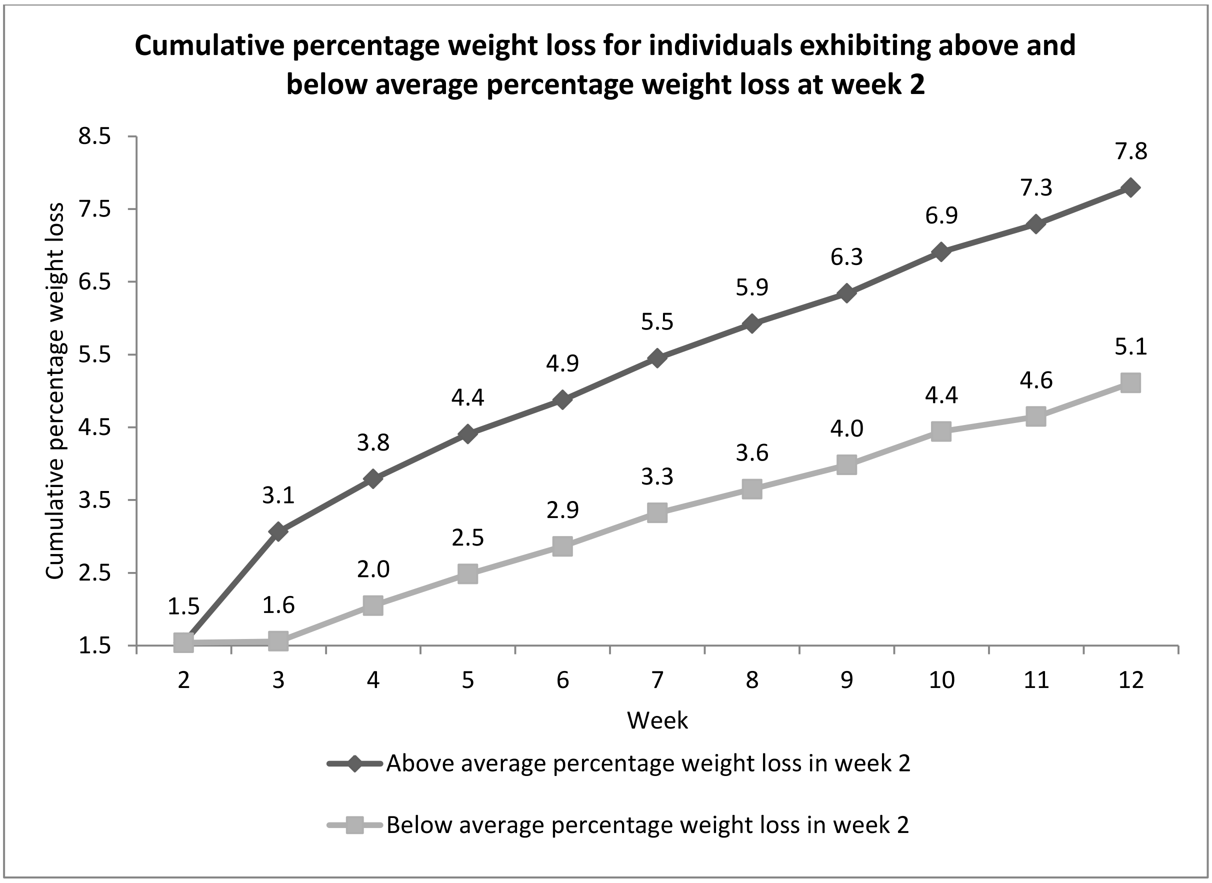


Figure 6.3: Cumulative percentage weight loss for individuals exhibiting above and below average percentage weight loss at week 2

Consistent attendance

Similarly, the results of analyses in Chapter 2 find consistent attendance (i.e. an attendance pattern with no breaks in week-by-week attendance) to be a strong predictor of successful outcomes. On all measures of success, i.e. percentage weight change, BMI change, significant weight loss and engagement at the latter stages of the programme, we find consistent attendance to be a significant predictor of success. Figure 6.4 presents the cumulative percentage weight loss for individuals who consistently and inconsistently attended the service. The dark grey line in Figure 6.4 plots the cumulative percentage weight loss for individuals who consistently attend. The lighter grey line plots the cumulative percentage weight loss for individuals who inconsistently attend. From the graph we observe an increasing disparity from a difference of 0.4 percentage points in week 3 to a difference of 2.3 percentage points in week 12 i.e. week-on-week individuals whom consistently attend outperform individuals who attend inconsistently resulting in increasing disparities over time.

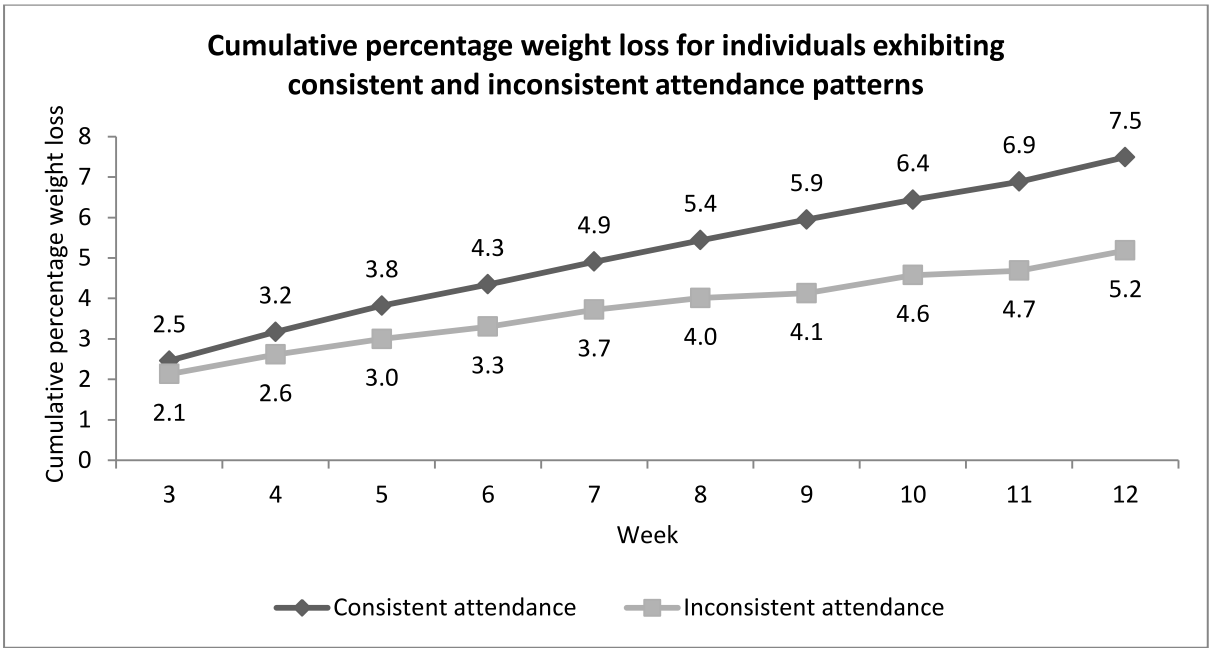


Figure 6.4: Cumulative percentage weight loss for individuals exhibiting consistent and inconsistent attendance patterns

The findings of initial weight loss and consistent attendance are of interest but must be interpreted with care. Firstly, it should be noted that whilst individuals who exhibit lesser weight loss at week 2 and/or attend inconsistently exhibit significantly lesser overall weight loss, on average both these groups are still achieving a greater than 5% reduction in initial body weight. Of importance is, therefore, whether the lesser weight loss experienced is due to a lesser desired overall reduction or whether individuals, in fact, desire higher weight loss but are unable to achieve it. To answer this question further research could compare weight loss goals set at the beginning of the service to measured outcomes in the latter stages to detect differences between the two. If individuals achieving a lesser weight loss had desired a greater change this would suggest that (1) the weight management service is not fully providing individuals with the capacity to match the complexities of the system and (2) the weight management service may result in the development of inequalities between individuals.

Identification of growing disparities between individuals presents an opportunity for weight management services to intervene. The weight management service studied in this thesis collects data on weight change in real-time and, therefore, has the ability to tailor an individual's experience based on these objectively measured outcomes on a week-by-week basis. As basic example, failure to attend a session could trigger communication to the individual to increase the probability of future attendance and engagement with weight loss behaviours. Whilst our research can support weight management services to identify who they should target, we can only hypothesise the drivers/mechanisms of action of observed behaviour (which we do so within discussions in our research chapters) based on the theoretical frameworks presented in Chapter 1. In other words, from our research we cannot provide empirically founded recommendations for the content of such suggested communications.

Deprivation

Of particular interest in Chapter 1 is the evidence of a relationship between deprivation and obesity (see Figure 1.3 to 1.6). In recognition of this relationship we include a deprivation variable within analyses i.e. the decile of deprivation for each individual based on home postcode. Key to our study was to examine whether weight management services exasperate weight related inequalities. Reflecting on our deprivation variable, we find no evidence of a relationship between the propensity to exhibit positive outcomes, considering both attrition and weight loss. This all-encompassing measure of deprivation, however, potentially misses some of the nuances of inequalities. This is evidenced in our findings of significant relationships between (1) education and weight loss outcomes and (2) the presence of children and weight loss outcomes and attrition.

Education

As stated in the summary of findings, more educated individuals, defined by the attainment of a degree level qualification, exhibit significantly greater weight loss in analyses in Chapter 2. The positive relationship between education and weight loss remains significant in analyses controlling for sample selection in Chapter 4. Reflecting back to discussions in Chapter 1 we observe a clear gradient in the prevalence of obesity from individuals with no qualifications to individuals with a degree level qualifications (see Figure 1.2), particularly among women. Whilst we utilise a binary variable within analyses in Chapters 2 and 4, we can spilt our findings into the same five categories of educational attainment previously presented in Figure 1.2 which explored obesity prevalence. Figure 6.5 presents the percentage weight loss at week 12 for each of the five categories of educational attainment. We reflect the pattern observed in the relationship between education and obesity prevalence (Figure 1.2) in the relationship between education and weight loss (Figure 6.5).

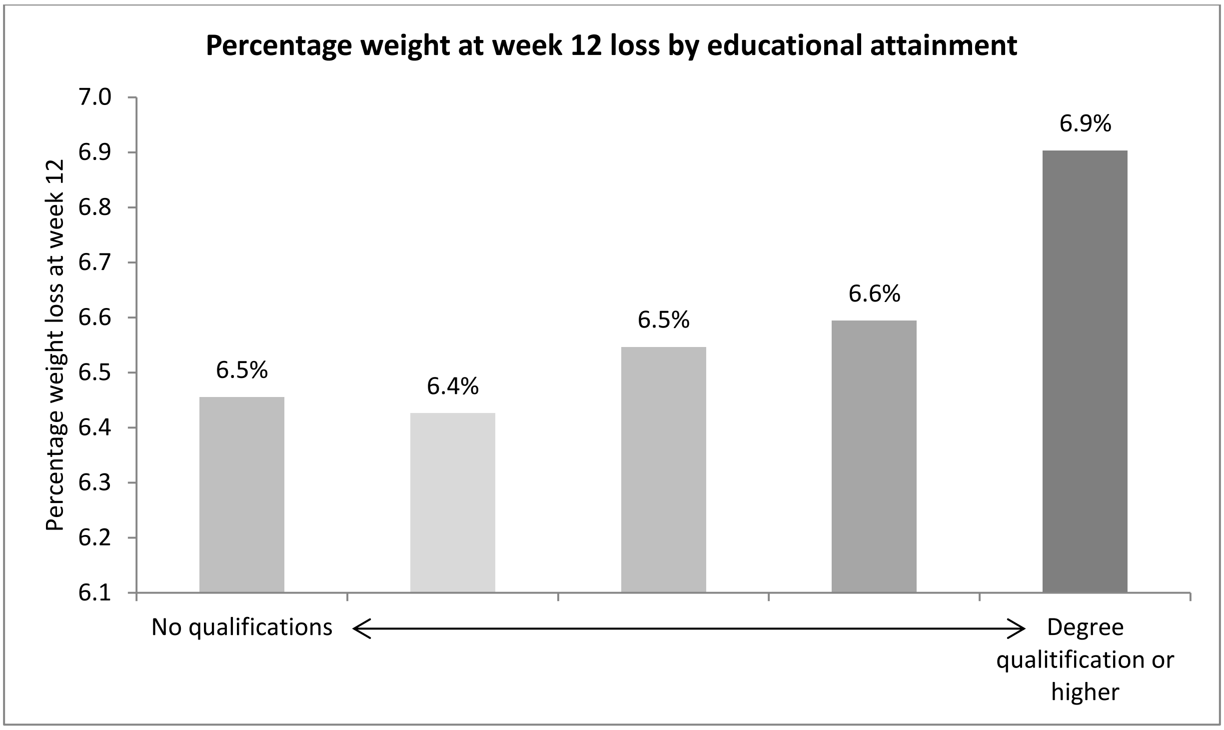


Figure 6.5: Percentage weight at week 12 loss by educational attainment

The relationship depicted in Figure 6.5 suggests the weight management service may be inadvertently contributing to widening health inequalities. If more educated individuals experience greater weight loss at a large scale (as is intended by weight management provision), this will subsequently increase the relative difference in obesity prevalence between those most and least educated. The 'inverse prevention law' refers to the principle that the availability and efficacy of preventative interventions are inversely associated with the needs of the population served (Gordon et al., 1999). In the current context the need for weight loss is greatest in the least educated population yet the intervention is most successful for those most educated, thus, generating an 'intervention-generated-inequality' (Lorenc et al., 2012). This concept is not unique to obesity with a number of studies raising concerns about public health interventions which may increase inequalities, whether this is inequalities in intervention efficacy, provision, access, uptake or compliance (Tugwell et al., 2006; White, Adams and Heywood, 2009; Graham and Kelly, 2004; Whitehead and Dahlgren, 2006; and Dahlgren and Whitehead, 2006). In their review, Lorenc et al. (2012) find evidence that media campaigns in particular increase inequalities although the authors note that for many interventions, data on potential intervention-generated-inequality is lacking. Of particular concern are interventions which negatively impact those at greatest risk and result in benefits to individuals at minimal risk of ill health.

In the current context of the weight management service, it is argued that all participants are at increased risk of ill health as the eligibility criteria for the service included a BMI threshold of $\geq$30. In Chapter 1 we present the relationship between BMI and risk of ill-health and discuss the appropriateness of using a BMI threshold of $\geq$30. Further, as presented in Figure 6.5, on average, least educated individuals do exhibit weight loss outcomes of between 6.4 and 6.5% reduction in original body weight. Our findings of significantly lesser weight loss amongst less educated individuals are, therefore, simply relative to the success of more educated individuals. We also find no significant evidence of an educational bias in individuals selecting into the latter stages of the programme, thus, can be fairly certain of a representative sample entering our weight outcomes analyses.

The issue of inequalities are, however, broader than the outcomes of the weight management service. Presented in Chapter 1, a significant societal cost of obesity is the resulting reduced productivity and increased unemployment. The foresight report (responsible for the production of the Foresight Map presented in Figure 1.1) suggests that the total economic impact of obesity on employment may be as much as £10 billion (McCormack and Stone, 2007). Whilst the relationship between unemployment and obesity is likely to be reciprocal, evidences suggests that, at least to a certain extent, weight loss positively affects the employment prospects of obese individuals (Reichert, 2015). In the context of our research it may be argued that relatively less successful weight loss amongst less educated individuals may exponentially lower the probability of employment in the short term and, thus, over time, may result in a higher dependence on state benefits due to decreased household incomes, savings and pension contributions and the relative increased risk of obesity-related conditions in the longer term (McCormack and Stone, 2007).

We now discuss our findings in the context of the complex system perspective. Of particular relevance are the two hypotheses (presented originally in Chapter 1) for the increased prevalence of obesity and relatively less successful weight loss outcomes experienced by less educated individuals. The first hypothesis is that these individuals are exposed to a greater number of obesogenic factors and the second hypothesis is that, regardless of frequency of exposure, these individuals are more vulnerable to obesogenic factors. Whilst we do not empirically test these hypotheses, as we do not find a significant relationship between weight loss and deprivation, employment or perception of the healthiness of one's local area, it is suggested that less educated individuals may lack the capacity to match the complexities of the system i.e. they are at an increased vulnerability to obesogenic factors rather than exposure to a greater number of factors. This hypothesis is supported in the literature by, for example, Vogel et al. (2016), who find mothers with low educational attainment evidence a greater susceptibility to less healthy supermarket environments than mothers with higher educational attainment. The authors suggest that higher educational attainment may be associated with greater psychological and financial resources which act as a protection against obesogenic factors in the environment

If the significant difference observed in weight loss outcomes is due to an increased vulnerability of less educated individuals, which weight management services are not able to fully compensate for, we risk disparities resulting from the intervention widening over time. Indeed, the difference in percentage weight loss between individuals with a degree and those without is 0.4% at the 12 week stage of the service (see Figure 6.5). Within the 292 individual for which we have 6 month weight measurements, this disparity has increased to 1.6%, with individuals with degree level educational attainment, on average, losing 10.1% of initial body weight compared to an average of 8.5% for individuals without a degree.

As discussed previously, the findings from our research can support weight management services to identify which individuals should be targeted, based on inequitable outcomes; however, we can only hypothesise the drivers/mechanisms of our observations based on theoretical frameworks and an understanding of complex systems. Further research is required to understand why we observe a significant difference in outcomes based on educational attainment. In principle, however, discussions suggest that in the short term there is a requirement for weight management service to strengthen and/or tailor their approach for less educated individuals in order to reduce potential intervention-generated-inequality. From a policy perspective our discussion provide additional support for the need to address wider systemic determinants of obesity if we are to create an environment supportive of equitable engagement in healthy behaviours rather than relying on individual’s capacity to resist such environments.

Children

Of further interest to discussions of inequalities are our findings regarding an association between weight loss and attendance and the presence of children. Specifically, we find some evidence of lesser weight loss and strong evidence of lower attendance amongst individuals with children. Throughout the thesis we have discussed the importance of exposure to the weight management service on weight loss outcomes. This is supported by discussions in Section 2.6.12 which presents the positive relationship between consistent attendance and greater weight loss. Significantly lower attendance amongst individuals with children, therefore, represents an intervention-generated-inequality with regards to compliance.

Within the literature there is no consistent evidence of the presence of children on increased risk of obesity. Whilst the weight management service may not be increasing any existing inequalities in adults, findings suggest there are potential impacts for the children. These are discussed further below.

Cross-sectional and longitudinal studies provide evidence that parental weight status (i.e. BMI $\geq$25) is a risk factor for overweight and obesity in children (Gibson et al., 2007; Maffeis, Talamini, & Tato, 1998; Schaefer-Graf et al., 2005; Wang, Patterson, & Hills, 2002; Whitaker et al., 1997). In fact, studies report that children with two obese parents are ten to twelve times more likely to be obese (Reilly et al., 2005 and Whitaker et al., 2010). Broadly, parental influence on child weight is thought to stem from both shared genetic and environmental factors (Whitaker et al., 1997). Further, childhood is a critical period for the development of health behaviours which persist over time. It is, therefore, unsurprising that overweight and obese children are at a greater risk of becoming obese adults, and have a higher risk of morbidity, disability and premature mortality in adulthood (NOO, 2016 and Cunnane, 1993).

Our findings that individuals with children exhibit lesser weight loss and lower attendance are, therefore, of importance due to the existing inequality between children with overweight and obese parents and children with healthy weight parents. Our research suggests that, even if obese parents attempt to lose weight, they struggle to engage weight management behaviours. Further, it is suggested that these behaviours may be transferred from parent to child and, therefore, whilst not necessarily increasing inequalities, it may be perpetuating existing disparities.

Reflecting back to discussions of education and outcomes, of interest is evidence that suggests that greater educational attainment in parents promotes the transmission of health to children i.e. for a variety of reasons, a strong positive relationship exists between parental education and childhood health (Currie, 2009).

Further, whilst a direct causal relationship between obesity in childhood and future employment outcomes has not been established, research finds that, in general, childhood ill-health plays an important role in future outcomes such as a lower probability of being employed in later life (Currie, 2009). In addition the evidence of a relationship between (1) childhood and adult obesity, and (2) between adult obesity and employment, provides support for the hypothesised relationship between childhood obesity and future outcomes (Cawley, 2004).

Current discussions raise two key concerns. Firstly, it is suggested that children with overweight or obese parents are at increased risk of obesity, which may be further aggravated by parental educational attainment, resulting in increasing inequalities amongst the younger generation. Secondly, discussions highlight the potential intergenerational transmission of inequalities due to the cyclical nature of (1) the suggested relationship between parental education and childhood obesity and (2) the hypothesised relationship between childhood obesity and future outcomes.

One caveat to discussions is that we do not collect information on the age of children in our study and, thus, we cannot know to what extent our concerns are realised. Further, one may argue that from a preventative perspective the observation of more successful outcomes in individuals without children is positive as it may be assumed that obesity is being tackled prior to potential pregnancy, thus, reducing the risk of maternal and foetal complications.

In conclusion to this section we present the implications for practice and policy resulting from discussions. As previously stated our research can support weight management services and policy to identify who should be targeted, however, we can only hypothesise the drivers/mechanisms of action of observed behaviour and make suggested recommendations based on these proposed hypotheses.

Utilising the COM-B theoretical framework it is suggested that the relationship between the presence of children and attrition may be due to a lack of physical capability (for example, parents may lack the capability to engage in weight management service due to childcare responsibilities) or psychological capability (for example, parental responsibilities may diminish cognitive capacity to engage in new weight-loss behaviours which contrast with existing habitual dietary activities). Recommendations for service provision may, therefore, include the provision of crèche facilities to increase physical capability and ensuring suggested behaviour change integrates with family life, thus, reducing cognitive requirement for engagement.

From our research we find educational attainment increases the probability of successful weight loss and in general seems to be a protective factor against the development of obesity. From a preventative policy perspective, it is therefore suggested that reducing disparities in the educational attainment of children may also reduce disparities in obesity prevalence. Singular policy interventions are, however, unlikely to be successful and discussions regarding the influence and complex nature of social and environmental factors contribute to the identified need for system wide change presented in Chapter 1. Policies to reduce educational inequalities must be complemented by policies to increase the capacity and capability of parents to match the complexities of the system and, thus, over time transfer such behaviours to their children. It is further argued that based on the hypothesised lack of psychological capability of parents to implement behaviour change strategies, policy that creates environments supportive of equitable engagement in healthy behaviours, rather than policies relying on individual’s capacity to resist environments, may be favourable.

Finally, we comment briefly on the role of obesity policy in the management of broader socio-economic inequalities. Evidence suggests that a cyclical, intergenerational transmission of socio-economic inequalities exists; however, there is currently a lack of empirical evidence regarding the extent to which health outcomes, and specifically weight-related outcomes, contribute to this observed pattern. It therefore may be premature to recommend health policies with the aim to tackle wider inequalities i.e. we cannot be certain that the introduction of policy to increase the efficacy of weight management in parents will lead to socio-economic benefits for the younger generation as they enter adulthood.

6.5 Obesity related stigma

From discussions of the literature in Chapter 2 we identify a positive relationship between obesity and depression whereby depression will increase an individual's risk of obesity by 58% (Luppino et al., 2010). Further, as stated above, we find evidence that individuals with depression are less likely to attend weight management services than individuals without a mental health condition. Our findings are reflective of the current literature which clearly points to a positive relationship between depression and attrition. As individuals with depression represent a population at greater need of weight management support, yet in practice are significantly less likely to attend, our findings represent an intervention-generated-inequality with regards to compliance.

A study comparing group weight loss support to self-help approaches found individuals partaking in group support lost more than three times the weight of the self-help group. If we assume depression reduces the probability of seeking support for weight management more broadly it is therefore suggested that the identified relationship between obesity and depression may, to some extent, result from a reduced probability of engagement behaviours which are more likely to lead to successful weight management.

Of importance to current discussions is the issue of weight stigma. As discussed in Chapter 1, obesity is often misunderstood to be solely a result of factors within personal control with little regard to the genetic, biological, social, economic and environmental factors of influence. Consequentially, obese individuals face discrimination due to a perception of, for example, laziness, a lack of self-discipline and unintelligence (Puhl and Heuer, 2010; Puhl, and Brownell, 2001; Puhl and Heuer, 2009 and Brownell, 2005). There is a further misperception that weight stigma motivates obese individuals to lose weight, however, there is growing evidence which suggests that weight stigma, in fact, perpetuates obesity and increases inequalities (Puhl and Heuer, 2010). In addition to discussions regarding weight stigma perpetuating unhealthy behaviours is evidence of the detrimental effect of weight stigma on psychological health. Of particular interest in the context of our findings is the evidence of weight stigmatisation as a significant risk factor for depression (Puhl and Heuer, 2010; Jackson, Grilo and Masheb, 2000; Friedman et al., 2005 and Myers and Rosen, 1999). Given the evidence it is argued that individuals with depression are at an exponential risk of obesity related ill-health due to a toxic combination of existing prevalence, intervention-generated-inequalities regarding compliance and a vulnerability to weight stigmatization which perpetuates the problem.

From a practice perspective, it is argued that the commercial providers of weight management service are aware of the detrimental impact of weight stigma on weight loss and have developed services which are non-judgemental and supportive of members. Given the evidence regarding the multitude of factors which influence obesity and weight loss, it is suggested that weight management providers may wish to ensure that approaches are not solely focused on nutritional and physical activity support but also provide individuals with coping strategies to avoid potentially detrimental social and environmental factors. The finding of a positive relationship between depression and attrition, presents an opportunity for improved provision to negate potential intervention-generated-inequalities. From a commissioning perspective parallel weight management and mental health support could, perhaps, be considered.

From a policy perspective, Puhl and Heuer (2010) make three recommendations to reduce weight-based stigma and discrimination:

1. Weight stigma should be addressed in obesity interventions and anti-stigma messages should be incorporated into obesity prevention campaigns.
2. Prevention efforts should focus larger-scale, coordinated policies that initiate social changes to help reverse the societal and environmental conditions that create obesity in the first place.
3. The introduction of legislation to prohibit weight-based discrimination.

(Puhl and Heuer, 2010)

The recommendations presented above are largely reflective of recommendations and discussions which are presented throughout this thesis; in particular recommendation 2. Regarding the first recommendation, however, we raise concerns regarding the efficacy of public campaigns to reduce stigma. This is due to the, previously stated, tendency for campaign to appeal to individuals whose beliefs already align with the messaging and, thus, the potential for such approaches to waste resources confirming current beliefs rather than changing perceptions. We do, however, endorse policy which targets health professionals behaviour by reframing obesity as a matter of clinical significance, thus, encouraging health care professionals intervene before the development of comorbidities.

We also raise concerns regarding the recommendation of legislative action as research suggests that previous legislative attempts to reduce discrimination against individuals with disabilities may have inadvertently increased inequalities (Bambra and Pope, 2007). Whilst legislation may force, for example, more equitable employment opportunities it is questioned whether such approaches will create the broader paradigm shift in attitudes which is desired. Without a change in the general understanding of the causes of obesity, such approaches risk aggravating broader weight discrimination due to an erroneous perception of undeserved favourable opportunities for obese individuals.

6.6 Prevention and economic benefits of weight management

A significant relationship between age and weight outcomes is found throughout our research chapters. In this section we reflect on these findings in the context of inequalities, behavioural theory, prevention and economic benefit.

Inequalities

Previously we discuss the concept of intervention-generated-inequalities whereby populations at higher risk benefit least from interventions, thus, increasing health and social inequalities. Generally, age and obesity prevalence are positively associated i.e. as age increases so does the prevalence of obesity (NOO, 2016). Within our research we find a positive relationship between age and weight loss, suggesting that weight management service support a reduction in age based weight inequalities.

Behavioural theory

Discussions regarding the relationship between age and weight loss, in particular, showcase why the thesis is greater as a whole than the sum of its part. In Chapter 1 (Section 1.7.3) we discuss how recommended behaviour change techniques provide evidence of 'what' changes behaviour but not 'why' behaviour has changed. Similarly throughout discussion within this chapter we repeatedly state that our empirical research presented in Chapters 2, 3 and 4 supports the identification of 'who' benefits from weight management services but does not empirically identify 'why' individuals should experience significantly different outcomes. Within Chapters 2 to 4 we draw upon behaviour change theory, presenting hypotheses for the observed findings. In Chapter 5, however, we begin to examine this question of 'why'. As stated, we find a significant positive relationship between increasing age and increasing weight loss both in Chapter 2 and persisting in Chapter 4 where we control for sample selection. Our discussion of the theoretical underpinnings focuses on the physical and psychological capabilities of older adults as a hypothesis for our observed findings. Specifically we suggest older individuals may benefit from stabilities such as living arrangements, employment and relationships which enable the formation of habitual healthy eating and physical activity behaviours (Chapter 2, Section 2.6.1). In Chapter 5 we find we find that older individuals with a BMI ≥25 are less risk averse than their healthy weight counterparts. Within discussions in Chapter 5 we outline the general relationship between age and risk aversion and suggest that the salience of risk from overweight and obesity may increase with age as, for example, individuals are exposed to greater incidence of obesity-related comorbidities either within themselves or within their social groups. Further, we suggest that as the salience of poor health outcomes increases, those who are risk averse begin to maintain a healthy weight or wish to lose weight whilst less risk averse individuals are more likely to become and remain overweight or obese. Our findings in Chapter 5, therefore, lead us to question whether the association between age and weight loss, observed in Chapters 2 and 4, could perhaps result from an increased probability for risk averse older adults to enter our sample due to a higher probability to engage in risk reducing behaviours. The combination of findings of the four research chapters allows for more robust recommendations of not only who to target but also a theoretical and empirical foundation for how and what activities may be required to ensure equitable access, compliance and outcomes amongst participants.

Prevention

Hypotheses regarding increasing risk aversion due to increasing salience of obesity-related comorbidities prompt discussions regarding the preventative nature of weight management services. Weight management services are classed as primary care (see Appendix 3), and within the stages of prevention model, (see Figure 1.7) are referred to a primary prevention as they aim to alter behaviours to reduce the risk of the development of obesity-related co-morbidities. As few medical restrictions to participation apply (see Appendix 5), however, we observe 42% of individuals starting the service with a pre-existing obesity-related comorbidity. Although NICE guidance (NICE, 2014) states that weight management services may benefit adults with comorbidities, the greater outcome of weight loss amongst this group is both the risk reduction of developing further comorbidities but also the management of existing conditions. Within the prevention model (Figure 1.7) this latter outcome is classified as tertiary prevention as the service is altering behaviours to reduce the impact of the condition on, for example, individual's function and quality of life (Nammi et al., 2004). Reducing the risk of complications from existing conditions is both beneficial to individual health and wellbeing but also economically sensible. Economic modelling suggests the NHS in England spends around £2.4 billion a year on inpatient care for individuals with diabetes. It is estimated that around £630 million is in excess of individuals of the same age and gender without the condition (Diabetes UK, 2014). From our research we find some evidence that individuals with existing conditions exhibit poorer weight loss outcomes compared to individuals who enter the service without a pre-existing comorbidity. Specifically, we find some evidence of lower weight loss amongst individuals with CVD and we find relatively strong evidence for an association between poorer weight loss outcomes and the presence of diabetes despite evidence of higher participation amongst this group. Of important, as previously discussed, is ensuring that ill-health is not exasperated amongst individuals with such existing conditions.

From a practice perspective, therefore, a key question is whether the relatively poorer outcomes amongst diabetics justify a distinctive intervention for this population. Reflecting back to discussions in Chapter 1 regarding statistical vs. clinical significance we find that whilst the difference in weight loss outcomes between diabetic and non-diabetic individuals is statistically significant, diabetic individuals, on average, lose a clinically significant 5.7% of original body weight by week 12 of the service. It is argued, therefore, that the approach of weight management services is of significant benefit to diabetic individuals but perhaps requires a more tailored approach. This has been precisely the action of the NHS who has commissioned the National Diabetes Prevention Programme (NHS England, 2016) which is essentially weight management services tailored to pre-diabetic individuals.

From a broader weight management programme perspective, the finding that 42% of individuals enter the service with a pre-existing comorbidity suggests more should be done to ensure health professionals are referring individuals earlier i.e. prior to the development of weight-related conditions. For weight management service this recommendation may be implemented by placing a greater emphasis on the referral of younger individuals. The risk of diabetes, for example, increases with age, with individuals over the age of 40 at particularly heightened risk (NHS, 2016). Therefore, targeting younger individuals refocuses the service as a primary, rather than tertiary, preventative approach.

This finding also has implications for policy. Forty-three percent of individuals enter the service with a pre-existing comorbidity despite the service primarily being designed as a primary prevention intervention. This suggests that there is a systemic failure within preventive policy which is allowing individuals to develop conditions prior to access to support. Ideally we would observe individuals accessing interventions prior to the development of conditions; however, it is argued that this requires a paradigm shift in how obesity is understood. From our research examining risk attitudes, for example, it is suggested that perhaps the risk of obesity only become salient with increased exposure to negative health outcomes. Indeed within qualitative studies 'impact on health' is often referred to as a strong motivation for weight loss (for example, Hankey, Leslie and Lean, 2002 and Reas, Masheb and Grilo, 2004). If, as is suggested in Chapter 5, individuals do not consider obesogenic behaviour as risky, they may be less likely to seek support until it is 'too late', thus, despite our recommendation above, health professionals may lack the opportunities for more preventative referrals. Discussion, therefore, provides further support for the need for investment into primordial preventative policies that aim to avoid the emergence of the social, economic and cultural patterns of living that are known to contribute to an elevated risk of disease.

Economic benefit

Returning to discussions of age and weight loss, here we briefly outline the wider benefit of targeting the younger population. In addition to the above discussions regarding health outcomes, there is also an economic argument for targeting younger individuals. In discussions of observed relationships between education, presence of children and weight loss outcomes we discuss the economic benefit of expected increased employment arising from a reduction in obesity prevalence. From discussion is it clear that the economic benefit of weight management is higher in young adults due to the increased years of employment expected from reduction is BMI. This is of course contingent on the longer term efficacy of weight management which has been previously challenged in Chapter 1 and commented on in Section 6.3.

6.7 Cost effectiveness of weight management services

The above section prompts discussions of the cost effectiveness of weight management services. Sample selection models presented in Chapter 4, whilst primarily designed to further explore the variables of interest presented in Chapter 2, report findings which are of importance to economic assessments of weight management services, such as cost-benefit analyses and research concerning return-on-investment. To demonstrate the implications of failing to control for sample selection we use an economic assessment model developed by PHE to compare the following outcomes over a 25 year period:

- Mean difference in BMI.
- Cumulative QALYs gained.
- Cumulative number of premature deaths prevented.
- Cumulative savings in healthcare costs.
- Cumulative savings in social care costs.
- Cumulative economic benefit of additional employment.

(NOO, 2016).

To generate these expected outcomes we enter the data from the weight management service into the model, such as the number of participants, the attrition rate, the average starting BMI and the average age of participants. Crucially, we run the model twice. Firstly using the expected BMI change at week 12 of -2.23 from OLS regression presented in Chapter 2 and, secondly, the expected BMI change of -1.57 from the sample selection model presented in Chapter 4. Table 6.1 presents the expected outcomes from these two models. From Table 6.1 we observe large variations in predicted longer term efficacy generated by OLS and FIML estimates. At year 25, for example, the cumulative economic benefit of additional employment based on findings from the OLS regression is £2,461,808, compared to a more modest £1,199,645 when utilising findings from the FIML model in Chapter 4.

	Estimates based on OLS regression results					Estimates based on sample selection regression results				
Key summary indicators	**Year 1**	**Year 3**	**Year 5**	**Year 10**	**Year 25**	**Year 1**	**Year 3**	**Year 5**	**Year 10**	**Year 25**
Mean difference in BMI across whole year[75]	-2.23	-2.04	-1.67	-0.74	0.00	-1.57	-1.37	-0.98	0.00	0.00
Cumulative QALYs gained[76]	11.5	90.4	172.5	320.7	417.1	8.2	64.2	118.8	188.5	215.6
Cumulative number of premature deaths prevented	0.0	0.0	0.3	3.3	39.8	0.0	0.0	0.2	2.2	20.0
Cumulative savings in healthcare costs	£1,072	£13,020	£43,169	£179,298	£483,096	£761	£9,270	£29,989	£111,430	£240,677
Cumulative savings in social care costs	£22,197	£165,891	£302,518	£502,344	£443,576	£15,754	£118,092	£208,668	£294,665	£231,743
Cumulative economic benefit of additional employment	£84,682	£658,947	£1,283,285	£2,482,237	£2,461,808	£60,778	£477,609	£899,465	£1,424,793	£1,199,645

Table 6.1: Comparison of two economic assessments of the weight management service from OLS and sample selection models

[75] Averaged across whole year, 1st year intake only.
[76] No discounting included.

Table 6.1 is useful for highlighting the impact of failing to control for sample selection, however, there are some critical assumptions made within the model which result in caution in interpretation of the precise figures. Of particular relevance to current discussions is the assumption of a population with no existing co-morbidities, which as discussed above is not the case for the weight management service examined in this thesis. Further, the cost benefit analysis is based on point estimates only and, therefore, does not consider the statistical uncertainty of the underlying parameters in the model. A suggested extension to this work is to reflect the statistical uncertainty following estimation methods presented in Harrison and Vinod (1992). Overall, however, we can recommend that possible issues of sample selection must be reflected in economic assessments of weight management services in order to obtain accurate estimates of short and longer term efficacy.

6.8 Limitations and further research

Limitations specific to each of the four areas of research are outlined in the individual chapters; therefore, here we reflect on the thesis as a whole to present limitations and suggestion for further research.

The first limitation of the research is the lack of longer term weight change outcomes. Longer term outcomes are important for economic assessments of weight management services but also for a longer term perspective of the nature of inequalities. In our discussion of education and weight loss we comment on the observed increasing inequality between the most and least educated individuals utilising weight measurements collected at the six month stage of the programme. From the perspective of weight loss a as preventative activity for long-term/lifetime risk reduction, however, measurements at six months are largely inadequate. Further research should, therefore, look to assess variables associated with weight status, weight loss and attrition over a longer period of time to allow for the identification of the changing nature (i.e. widening and narrowing) of inequalities.

In Chapter 1 we introduce the Foresight Map and discuss the nature of complex systems. Throughout our research we identify several variables which exhibit a significant relationship with weight loss. Within this final chapter we discuss how the presence of several variables may exponentially impact weight loss outcomes resulting in the disproportionate success of some individuals and, thus, the widening of inequalities. A key advancement on our research is, therefore, further examination of interactions between variables. This could be achieved either through the implementation of systematic iterations of interaction terms or via a theoretically driven exploration of the effects of combinations of variables. Whilst the former is more comprehensive, given the number of variables of interest, this approach will be complex and time consuming.

As stated throughout this chapter our research can identify who should be targeted but not why we observe disparities between populations. We begin to address this limitation in Chapter 5; however, as we only consider interactions between BMI and gender and BMI and age we are unable to comment further on many of the identified important variables of interest such as education and presence of children. Within Chapter 5 we do collect measures of education and presence of children. Further research could, therefore, utilize the data available and follow the analytical approach of Chapter 5 to examine the interaction between education and BMI and the presence of children and BMI.

As previously stated, there is great value in the joint presentation of the findings from the four research chapters as each builds upon the findings of the previous to present a rich and comprehensive assessment of variables associated with weight status, weight loss and attrition. As the two populations studied in Chapters 2 to 4 and 5 are, however, different, we can only make suggestions as to why we observe disparities between populations in the earlier chapters. Further research into weight management services could, therefore, collect the variables of interest identified in Chapter 2 and also repeat the risk aversion and time preference tasks presented in Chapter 5 amongst weight management participants. This approach would allow researchers to identify both who is more likely to lose weight and attend services but also directly understand why. If future research takes this approach we would also include recommendations made in Chapter 5 regarding the ability to test for evidence of hyperbolic discounting and lotteries with the prospect of losing money.

Beyond time and risk preferences, behavioural economics is beginning to provide researchers with elicitation methods and models for other factors such as social preferences, overconfidence and even emotional response (DellaVigna, 2009). There is a substantial opportunity to utilise such methods to complement existing qualitative, often self-reported, preference elicitation method used within the psychological literature.

In conclusion, our research furthers the understanding of variables associated with weight status, weight loss and attrition. Future research needs to bring together not only who may suffer from weight-related inequalities but when (i.e. analyses over longer time horizons) and, critically, why. From a policy perspective, however, it is expected that the key question will be ‘what’ works. This policy priority can already be observed in the growing popularity and utilisation of RCTs to evaluate the behavioural outcomes of policy interventions. Whilst largely these RCTs are based on theoretical (and sometimes empirical) understanding of drivers/mechanisms of behaviour we have previously discussed the risk of simply understanding what works but not why it works.

7. Appendix

Appendix 1: Background to obesity: The national and local perspective

Problem context

Adult obesity is associated with a significant decrease in life expectancy. Obesity also presents a huge psychosocial and social burden, often resulting in poor quality of life, social stigma, low self-esteem and depression. It is a primary underlying factor in numerous diseases including: type 2 diabetes; heart disease and stroke; osteoarthritis of the hips and knees and some cancers.

National costs

Estimated current cost of obesity and overweight is between £6.6 and £7.4 billion annually in the UK, but more than double by 2050. Wider economy costs (sickness/ reduced productivity) will rise to £50 billion by 2050 (Jebb et al., 2007).

Weight classifications

In adults, weight is most commonly assessed using BMI classification. BMI is calculated as weight in kilograms (kg) divided by height in metres squared (m^2).

- Underweight: BMI <17.9
- Healthy weight: BMI 18-24.9
- Overweight: BMI 25-29.9
- Obese: BMI 30-39
- Morbidly obese: >40

Local Context

In 2011, the combined population of County Durham and Darlington was approximately 650,000. At this time, the best estimate of obesity prevalence was data from the revised Health Survey for England 2006-2008 (APHO, 2014) which reported 28.6% of the population of County Durham and 27.6% of the population Darlington were obese. In comparison, the national (England) prevalence was estimated to be 24.2%. More worryingly, the available data showed increasing obesity prevalence over time in both County Durham and Darlington.

Whilst more concentrated local level obesity prevalence data did not exist, other data (such as incidence of diabetes, obesity related hospital episodes and GP registered patients recorded as obese) suggested widespread geographical variation in obesity prevalence within County Durham and Darlington. This variation is acutely linked to other inequalities. These are, broadly speaking:

- Inequalities in opportunities such as income, employment, education, employment and the environment (the wider determinants of health).
- Inequalities in lifestyle choices such as participation in physical activity, food choices and alcohol consumption.
- Inequalities in access to healthcare services.

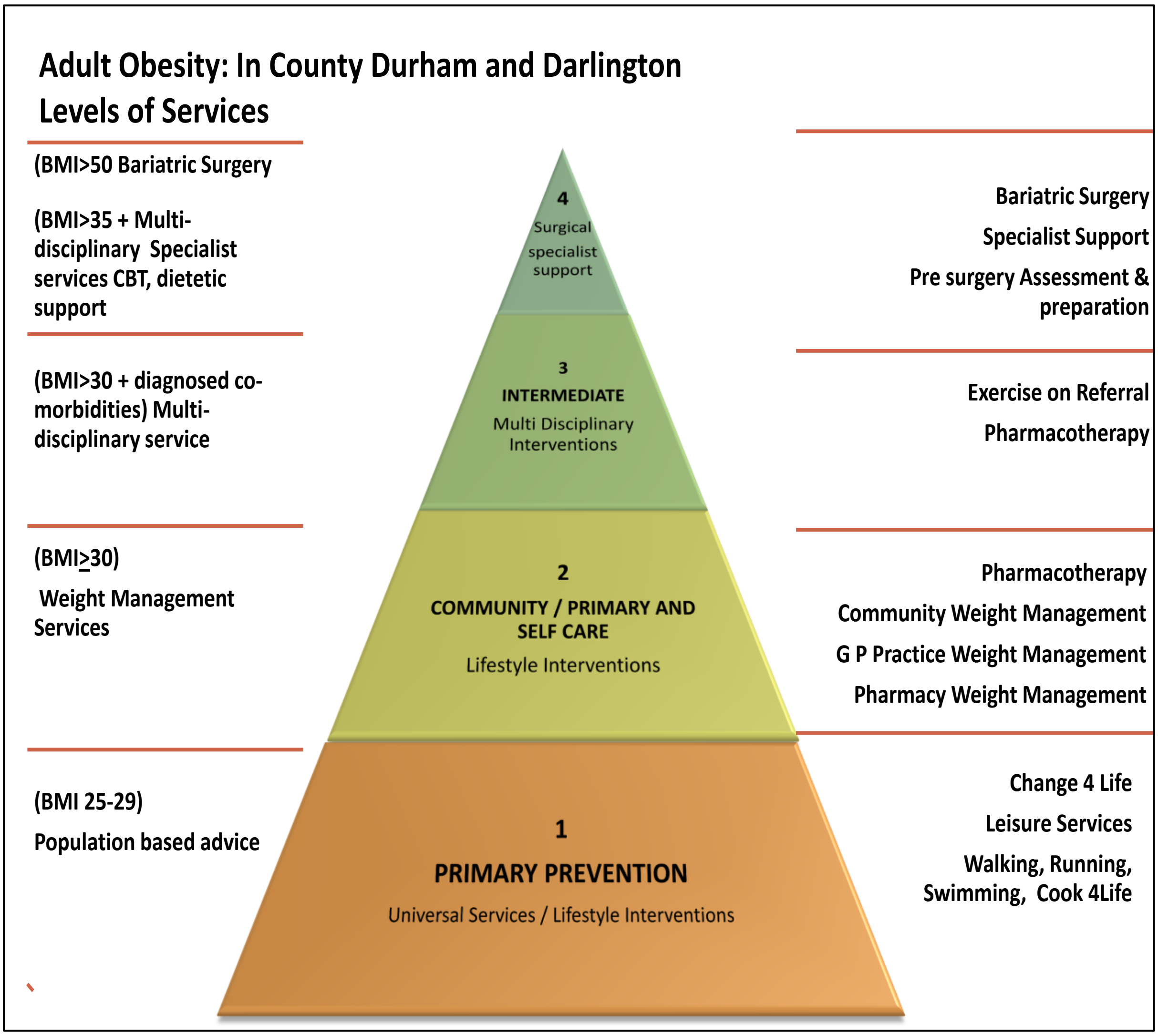
Appendix 2: Needs assessment for obesity treatment in County Durham

Based on prevalence data and data recorded by local healthcare professionals the demand for weight management services was expected to be high.

Local services for the management of obesity were mapped to gain an understanding of how obesity needs were being met and to identify gaps in service provision. The outcome of this activity is outlined in Appendix 3. The mapping activity identified good service provision at tiers 1, 3 and 4, however, a lack of effective and geographically consistent provision at tier 2. In other words, within County Durham and Darlington there was a lack of services, often referred to as "lifestyle intentions", specifically designed for individuals who are obese (BMI >30) but do not have diagnosed complex co-morbidities such as un-managed diabetes or heart conditions, thus, requiring non-surgical weight reduction.

As a result the NHS sought to commission a provider of weight management services to fill this gap in provision and so a team, including myself, were brought together to realise the development and implementation of the full service model.

Appendix 3: Tiers of obesity treatment mapped to service provision



Appendix 4: Referral Form for the weight management programme

Patient Information

First name		Telephone			
Middle name					
Surname		Email			
Address line 1		Preferred contact	☐ Post	☐ Telephone	☐ Email
Address line 2		DOB (DD/MM/YYYY)			
Town/City		Age			
Postcode		Gender (M/F)			

Reason for referral

☐ Self-referral (patient request)
☐ Health professional referral
☐ Patient advised to lose weight for underlying health condition
☐ Weight loss required for health intervention e.g. IVF treatment, gastric band operation
Other (please state)

Patient Measurements

Height (m)   Weight (kg)   BMI   Blood Pressure

Medical conditions

☐ >20% CVD risk	☐ Stroke	☐ Heart disease	☐ Arthritis	☐ Hyperlipidaemia
☐ Hypertension	☐ Asthma/COPD	☐ Depression	☐ Musculoskeletal	☐ Other (state)
☐ Diabetes	☐ Joint problems	☐ Stress/Anxiety	☐ Back problems	

Other medical conditions:

Further information

Alcohol consumption (units per week)   Smoking (cigarettes per week)

Disability

Under the disability discrimination act 1995, disability is defined as a physical or mental impairment that has a substantial and long term adverse effect on a person's ability to carry out day to day activities. Does the patient consider themself to be disabled by the act described above?

☐ No   ☐ Yes   ☐ Prefer not to state

Ethnicity

☐ White (English/Welsh/Scottish/Northern Irish/British/Irish/Gypsy or Irish Traveller)
☐ Mixed/multiple ethnic groups (White and Black Caribbean / White and Black African / White and Asian)
☐ Asian/Asian British (Indian, Pakistani, Bangladeshi, Chinese)
☐ Black/African/Caribbean/ Black British
☐ Other ethnic group (please state)

Referrer Information

Referrer name		Address line 1	
		Address line 2	
		Town/City	
		Postcode	

Appendix 5: Physical health exclusion criteria

Four exclusion criterions, based on an individual's health status, were established:

1. Individuals under the age of 18.
    - Due to the differing recommended approached to weight management for adults and children the service was restricted to individuals aged 18 and over
2. Pregnant women.
    - Guidance recommends that pregnant women do not attempt to lose weight. Weight management support for pregnant women was expected to be provided through maternity services.
3. Individuals with chest pain or breathless on exertion, currently participating in the cardiac or pulmonary rehabilitation programme and/or with uncontrolled hypertension.
    - These conditions in combination with participation in the programme may result in harmful health outcomes.
4. Patients diagnosed with an eating disorder.
    - Patients with eating disorders are not suitable for universal weight management services. Specialist support should be sort.

Appendix 6: Guidance to healthcare professional for effective referrals

monitoring and re-referral

Quarterly feedback will be made available to approved health professionals who refer patients into the Weigh-Less Scheme.

The feedback provided will be a general overview only, however, more enhanced data may be requested from the Weigh-Less Scheme hub and shared in line with appropriate data protection rules.

Patients may be re-referred into the Weigh-Less Scheme after 12 months from date of their first session.

Each patient will be eligible for a maximum of one referral in any 12 month period.

referral agency guidance

All health professionals wishing to refer individuals must be registered with the Weigh-Less Scheme. Upon registration you will be issued with all the resources needed to start referring into the scheme. (All referring agencies must have an nhs.net or a gcxs secure email account and complete a scheme registration form)

Health professionals should also make themselves familiar with the acceptable referrals and exclusion criteria set out in this document.

Weigh-Less Scheme Hub:
0191 372 9158
Monday to Friday
For more information contact
jparnaby-gcsx@durham.gcsx.gov.uk

Individuals registered with the Weigh-Less Scheme can take advantage of a special physical activity offer following their slimming on referral programme.

fit4life
4 steps to fitness

step 1
Set your goals
1 x free 1:1 session

step 2
Guided introduction to fitness
3 x free 1:1 sessions

step 3
Supported 6 week fitness programme only £30.00

step 4
Sustainable fitness membership*
Includes 1 month free fitness

*Terms and Conditions apply

May 2012

weigh-less scheme

Professional Guidance

Slimming on Referral Pathway

What is the Weigh-Less Scheme?

The Weigh-Less Scheme is a free 12 week slimming on referral opportunity for individuals identified as needing help with weight loss. Support and advice about diet, physical activity and goal setting is offered by trained group leaders to help kick start a healthier lifestyle.

How should I assess a person who is overweight?

- Assess underlying causes and comorbidities and the risk of developing complications of obesity.
- Assess lifestyle in terms of diet and exercise.
- Assess the potential health benefits of weight loss to the person.
- Assess the person's feelings about being overweight and willingness/motivation to lose weight

How should I approach the issue of weight with someone?

- Clinical judgement should be used to decide whether to measure a person's BMI. Opportunities include at registration to the practice and at consultations for conditions related to obesity.
- Approach the subject of weight carefully because people may be sensitive about discussing it, or feel that their presenting problem is being overlooked.
- Offer to discuss their measurements, and if their BMI is in the overweight or obese category, discuss why excess weight can be problematic and why gaining weight may increase risks to health.
- Make the person aware of the benefits of modest weight loss, particularly if they are obese.

How to assess a person's readiness to lose weight?

Questions which may help to clarify a person's readiness to lose weight include:

- Are you concerned about your weight?
- How important is it for you to lose weight at the moment?
- Do you believe that you could lose weight?
- Explore barriers to lifestyle change, for example: Lack of knowledge or lack of time; Cost and availability of healthy foods and opportunity for exercise; Low levels of fitness, disability and/or low self-esteem/assertiveness

Not ready to lose weight

Provide Patient with Change4Life Swap it Don't Stop it booklet

Ready to lose weight

Send electronic referral to Weigh-Less Scheme Hub

Provide patient with Weigh-Less Scheme Leaflet and advise patient to telephone the Hub to proceed with referral

how to refer into the weigh-less scheme

All referrals must be submitted and completed on the appropriate referral form. The form should be sent electronically to the Weigh-Less Scheme Hub.

The Weigh-Less Scheme Hub will receive all referrals, however, individuals referred are responsible for making contact with the Hub.

It is expected that individuals will attend a slimming on referral service for a period of 12 weeks for 1 hour a week. Advice and support will focus on weight management interventions which include behaviour change strategies, physical activity and nutrition.

Following the 12 week programme individuals will be offered an exit interview with the service provider with the following options available to them:

- Continue with current or alternative service as paying member.
- Access other lifestyle services such as physical activity opportunities.
- If weight loss has not been achieved the individual may be referred back to the health professional for advice and support.

All patients registered with the Weigh-Less Scheme will be invited to a free return visit by the service provider at 6 months to monitor patient progress.

acceptable referrals:

1 Individuals must be 18 years and over and registered to a GP practice in County Durham or Darlington.

2 Individuals must also have a BMI of over 30 but not greater than 35.

3 Individuals must be motivated to change.

unacceptable referrals:

The following are considered unacceptable for the Weigh-Less Scheme:-

- Patients under the age of 18.
- Patients with a BMI less than 30.
- Patients with a BMI greater than 35.
- Pregnant women.
- Patients who have accessed the Weigh-Less Scheme within the previous 12 months (maximum of one referral into the service per patient per year).
- Patients with uncontrolled hypertension. (160/100) unless assessed and approved by GP.
- Patients with chest pain/breathlessness on exertion unless assessed and approved by GP.
- Patients currently participating in Cardiac/ Pulmonary or other specialist rehabilitation programmes.
- Patients who have been identified as having an eating disorder.
- Patients who have paid to attend commercial weight loss programmes within the previous 12 weeks.
- Patients currently participating in the exercise on referral schemes within County Durham and Darlington.
- The Hub will try where possible to ensure that inappropriate referrals are informed of alternative options, this may include sign posting to other services.

Appendix 7: The service specification for the weight management service

Care Pathway/Service	**Level 2 Community Weight Management Service Adults**
Key Service Outcomes	
To reduce the prevalence of obesity by offering support to patients who are obese in order to achieve and maintain a healthy weight and improve their health: • 50% of registered patients to have completed the programme (10 out of 12 weeks). • All patients who have completed the programme to have a weight loss ≥ 5% of their baseline body weight.	
1. Purpose	
1.1 Aims and objectives 1.1.1 This specification is for the provision of a community weight management service for patients aged 18 years or over, with a BMI ≥ 30 and not greater than a BMI of 35 across County Durham and Darlington to receive support in order to achieve and maintain a healthy weight and improve their health. The service will incorporate the three elements which are essential to weight loss – dietary advice, behaviour change and physical activity. 1.1.2 This document describes the service level and quality to be commissioned. The specification is set out in such a way as to encourage innovation on the part of the provider service in developing a Community Weight Management Service. 1.2 National/local context and evidence base 1.2.1 The combined population of County Durham and Darlington is approximately 650,000 and the numbers of obese adults is increasing. Data from the Health Survey for England 2006 – 2008 models estimate the prevalence of obesity in County Durham and Darlington to be at 27.9% and 26.2% respectively compared to the England average of 24.2 %. Both figures demonstrate an increase on the previous year's data and this is in line with the national data trend. 1.2.2 Based on national Health Survey data and local QOF data it is estimated that demand for weight management services could be high and therefore it is vital to develop a pathway which addresses need at a population level, maximising opportunities for brief interventions as well as prioritise development of level two weight management services. 1.2.3 The commissioning of level two weight management services has been identified as a priority, however there is on-going work to review the current Adult Obesity Pathway and ensure that the model of service provision takes into consideration those with varying needs. 1.2.4 Adult obesity is associated with a significant decrease in life expectancy. Obesity also presents a huge psychosocial and social burden, often resulting in poor quality of life, social stigma, low self-esteem and depression. It is a primary underlying factor in numerous diseases including: type 2 diabetes; heart disease and stroke; osteoarthritis of the hips and knees and some cancers. 1.2.5 Estimated current cost of obesity and overweight is between £6.6 and £7.4 billion annually in the UK, but more than double by 2050. Wider economy costs (sickness/ reduced productivity) will rise to £50 billion by 2050 (The Foresight Report, Oct 2007). 1.2.6 In adults, the diagnosis of obesity is most commonly made using BMI levels. BMI is calculated as weight in kilograms (kg) divided by height in metres squared (m2). • A BMI of 25-29.9 kg/m2 is overweight. • A BMI of 30-34.9 kg/m2 is obese (I). • A BMI of 35-39.9 kg/m2 is obese (II). • A BMI of ≥40 kg/m2 is obese (III) or morbidly obese meaning that weight is a real and imminent threat to health 1.2.7 The National Obesity Observatory has highlighted the best available evidence to justify well-targeted action to manage and treat adult obesity. NICE Guidance (2006) CG43 Obesity	

guidance on the prevention, identification, assessment and management of overweight and obesity in adults and children suggests that effectiveness is enhanced when people:

- understand the likely impact of their behaviour on their health
- feel positive/optimistic about changing their behaviour
- make a personal commitment to change
- set goals to undertake specific actions over a specified time
- plan changes in terms of easy steps
- plan for events or situations that might get in the way of change
- share their behaviour change goals with others

1.2.8 The Observatory recommends that all new programmes, for which evidence of effectiveness does not already exist, are thoroughly evaluated. Guidance on evaluation is available in the NOO Standard Evaluation Framework15 http://www.noo.org.uk/core/SEF.

1.2.9 Within County Durham and Darlington, there are widespread geographical health variations. The reasons for the differences in health within County Durham and Darlington and between County Durham and Darlington residents and the rest of England are complex. However these differences can be explained by:

- Inequalities in opportunity – poverty, family, education, employment and environment (the wider determinants of health).
- Inequalities in lifestyle choices – smoking, physical activity, food, drugs, alcohol and sexual activity.
- Inequalities in access to services for those who are already ill or have accrued risk factors for disease.

1.2.10 This service will support a reduction in health inequalities by ensuring resources are targeted to priority communities and to areas that have been identified as having the highest burden of disease. Data from the health survey for England (2006 - 2008 revised), models the prevalence of obesity in adults in County Durham and Darlington to be 28.6 and 27.6 respectively.

2. Scope

2.1 Service Description

2.1.1 Individuals who fit the criteria in section 3.5, will be offered a place on a twelve week, community weight management programme which provides patients with the opportunity, education, support and skills to help them lose weight, effectively manage their own weight and maintain any lifestyle changes. The service will be group sessions where a number of like-minded individuals can get together with a group leader, to review dietary goals, receive support from the leader and other group members and to receive personal advice about dietary modification, physical activity and behaviour change. Patients who meet any of the exclusion criteria (see section 2.2) must not be referred into and accepted into this service.

2.1.2 This service is available to all patients aged 18 years or over, with a BMI equal to or greater than 30 and not greater than 35.

2.1.3 The provider of this service will:

2.1.3.1 Provide individuals with opportunities to be weighed weekly, have progressive goals set and to share difficulties.

2.1.3.2 Negotiate an individual plan with each patient to enable weight loss to occur,

2.1.3.3 Give advice to the individual on an appropriate, calorie reduced diet.

- Give culturally appropriate information to patients about treatment and care.
- Ensure that information given to patients is accessible to people with additional needs such as physical, sensory or learning disabilities, and to people who do not speak or read English.
- Follow NICE guidance (CG43) where appropriate

2.1.3.4 Encourage or enable individuals to take part in regular physical activity.

2.1.3.5 Set individual goals at the initial visit and to review these goals weekly (goals to be on weight loss, diet, physical activity and behaviour change).

2.1.3.6 Support individuals to make behaviour change to bring about weight loss e.g., self-monitoring of behaviour, ensuring social support, reinforcement of changes, relapse prevention including strategies for dealing with weight regain and identifying potential barriers to lifestyle changes.

2.1.3.7 Follow-up non attendees after 2 weeks of not attending meetings.

2.1.3.8 Invite patients back to the service for a free of charge weight measurement 6 months following registration.

2.1.3.9 Facilitate a survey of patient experience on behalf of the commissioner of this service.

2.1.3.10 Maintain records of the service provided, incorporating all known information relating to any significant events.

2.1.4 Clinical Audit: the provider agrees to comply with the NHS complaints procedure if dealing with service user complaints.

2.1.5 Corporate Governance: The provider will commit to meet with the commissioner on a six monthly basis in the first instance in order to ensure a cycle of continuous improvement which will be informed by patient experience survey as well as performance data

2.1.6 Information Governance
In line with data protection and information governance, people accessing the service will need to be made aware of the nature of all information collected and the purpose for which this is collected.

2.1.7 The service provider must not share any information with other services without prior written approval from the commissioner of this service, and any information sharing must be fully explained and agreed by the individual.

2.1.8 The provider of this service will not administer or prescribe any medicines.

2.1.9 The service provider will be expected to collaborate with the commissioner to advertise the service to all stakeholders.

2.2 Any exclusion criteria

2.2.1 Patients under the age of 18

2.2.2 Patients with a BMI less than 30

2.2.3 Patients with a BMI greater than 35

2.2.4 Pregnant Women

2.2.5 Patients who have accessed the County Durham and Darlington Weigh-Less Scheme within the previous 12 months (maximum of one referral into the service per patient per year)

2.2.6 Patients with uncontrolled Hypertension BP>160/100 unless referred by GP

2.2.7 Patients with chest pain/breathless on exertion unless assessed and referred by GP

2.2.8 Patients currently participating in Cardiac/Pulmonary Rehabilitation Programme

2.2.9 Patients who have been identified as having an Eating Disorder

2.2.10 Patients who have paid to attend commercial weight loss programmes within the previous 12 weeks

2.2.11 Patients currently participating in exercise on referral schemes within County Durham and Darlington

2.3 Geographic coverage/boundaries

2.3.1 Service provision will be located within County Durham and Darlington.

2.4 Whole system relationships

2.4.1 The provider will be expected to have a close working relationship with all healthcare providers relevant to the patient pathway.

2.5 Interdependencies and other services

2.5.1 The community weight management service will be integral to the County Durham and Darlington Adult Obesity Pathway. There are potential links with the following services:

- GP services
- Local authority

- Sport and Leisure services
- Health Improvement Service Providers
- Pharmacies
- Voluntary sector

2.6 Relevant networks and screening programmes

2.6.1 The provider should ensure the service is aligned with government messages and social marketing initiatives such as:

- 5 A DAY(five portions of fruit and vegetables a day)
- The Chief Medical Officer (CMO's) recommendation for physical activity (at least 30 minutes a day of at least moderate intensity activity on five or more days of the week)
- Food Standards Agency Guidelines (Eat Well Plate)
- NHS guidelines for alcohol consumption, calorific values of alcohol and the link to weight gain
- Change4Life national social marketing campaign

2.7 Training/ education/ research activities

2.7.1 Staff who advise people on diet, weight and activity need appropriate training, experience and enthusiasm to motivate people to change. The provider must be able to evidence training, competency and maintenance of competency which may be requested by NHS County Durham and Darlington at any time.

2.7.2 The provider must ensure that staff responsible for leading and delivering the weight management programme have the required Criminal Records Bureau (CRB) checks in order to comply with local safeguarding arrangements as stated in section 5.3.1 of county Durham and Darlington's community contract.

3. Service Delivery

3.1 Service model

3.1.1 The patient aged 18 or over, with a BMI equal to or greater than 30 and not greater than 35, (who does not meet any of the exclusion criteria in section 2.2) will be offered a place on a community weight management programme by their GP or appropriate registered community referrer (such as Community Pharmacy and Healthcare practitioners trained to offer Community Health checks). If the patient agrees, the GP/community referrer will refer the patient to the Weigh-Less Scheme hub.

3.1.2 The Weigh-Less Scheme Hub will receive all referrals from registered referral agencies however the patient will be responsible for making contact with the hub to discuss appropriate provision.

3.1.3 The Weigh-Less Scheme Hub will send confirmation to the patient and details relating to the chosen weight loss provider.

3.1.4 The patient will register with the provider of their choice within 4 weeks of registering with the Weigh-Less Scheme.

3.1.5 It is expected that patients will attend the community weight management service for a period of twelve consecutive weeks for one hour per week. The community weight management classes will focus on weight management interventions which include behaviour change strategies to increase people's physical activity levels and/or decrease inactivity; improve eating behaviour and the quality of the person's diet; reduce calorie intake.

3.1.6 Advice needs to be tailored for different groups. This is particularly important for people from black and minority ethnic groups, vulnerable groups (such as those on low incomes) and people at life stages with increased risk for weight gain (such post pregnancy, at the menopause or when stopping smoking).

3.1.7 The 12 week community weight management service will:

- Provide patients with opportunities to be weighed weekly, have progressive goals set and to share difficulties

- Develop an individual plan with each patient to assist with weight loss
- Give advice to patients on an appropriate, calorie reduced diet
- Encourage and enable patients to take part in regular physical activity
- Set patients goals at the beginning of the course and to review these goals weekly (goals will be on weight loss, diet, physical activity and behaviour change)
- Have regular discussions with patients using motivational interviewing techniques, to support them to make behaviour change to assist with weight loss

3.1.8 Following the 12 week community weight management programme (Weigh-Less Scheme) patients will be offered an exit interview with the service provider and have their options explained to them. The patient will be discharged from the County Durham and Darlington Weigh-Less Scheme and will have the option to:

- Self-refer and continue with the existing service provider as a paying member
- Self-refer and register with a weight management service of their choice as a paying member
- Access universal community lifestyle services such as walking groups, leisure services or community food and health services
- Pursue their personal weight loss programme independent of support
- Visit their GP for further appropriate advice and guidance

3.1.9 Patients who choose to self-refer into any weight loss service must do so through a private arrangement with the provider. Any arrangement made between a self-referring patient and the provider is not covered by the terms and conditions set out within this contract.

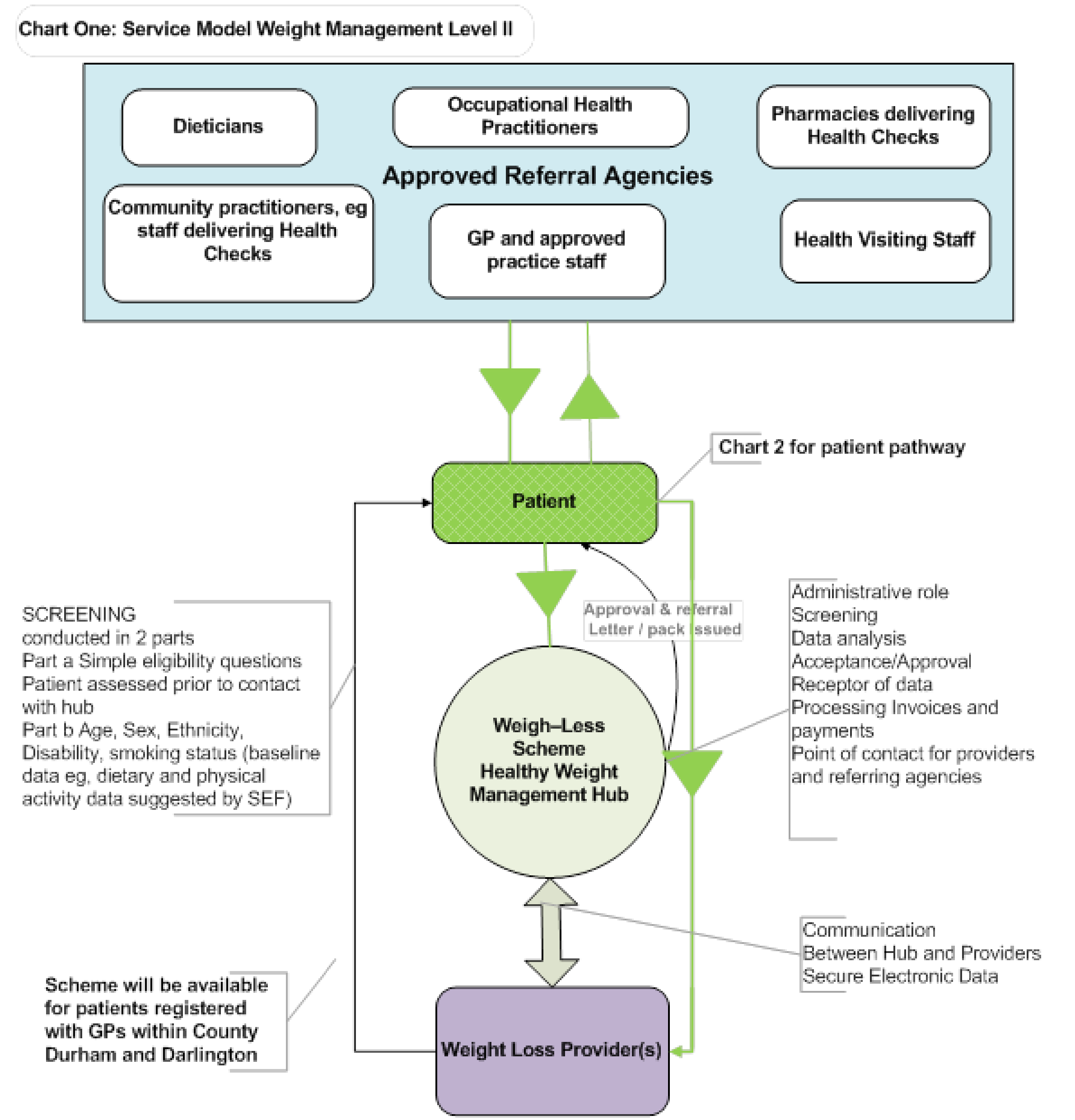
3.1.10 All registered patients will be invited back for a free return visit to the service to be weighed 6 months (24 weeks) from initial registration with provider and no later than 7 months (28 weeks) from initial registration in order to:

- monitor patient progress and;
- Provide accurate data to the commissioner.

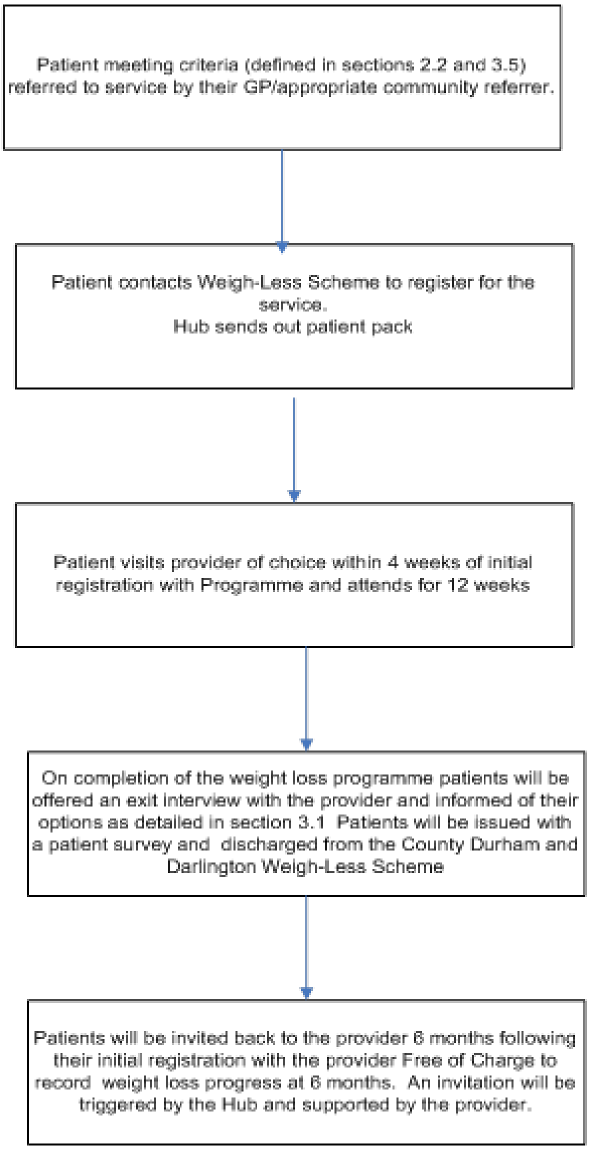
3.1.11 Patients may be re-referred into the Weigh-Less Scheme via their GP and registered and approved referral agencies such as pharmacies accredited to deliver health checks in County Durham and Darlington after 12 months from date of first registration with providers.

3.1.12 Each patient will be eligible for a maximum of one referral in any 12 month period.

3.1.13 See Chart One: Service Model



3.2 Care Pathway (on next page)



3.3 Location(s) of service delivery

3.3.1 The service will be provided from appropriately equipped premises within the boundaries of County Durham and Darlington

3.3.2 The provider will ensure that accurate information relating to location and days / hours of service delivery is provided to the weigh-less hub no less than one week in advance of commencing delivery or changes to delivery times.

3.4 Days/hours of operation

3.4.1 The service will run flexibly throughout the whole year, including evening sessions and weekends. It is expected that patients will attend the community weight management service for a period of twelve consecutive weeks for a minimum of one hour per week. Providers will need to develop programmes based on patient demand.

3.5 Referral criteria and sources

3.5.1 Individuals 18 years and over registered to a GP practice in County Durham and Darlington with a BMI equal to or greater than 30 and not greater than 35 will be accepted onto the programme. Referrals will be made by GPs and approved community referrers (such as Community Pharmacy and Healthcare advisors trained to offer Community Health checks) in County Durham and Darlington. There is likely to be a phased approach to approving referral agencies by the commissioners of the service as the service develops.

3.6 Referral processes

3.6.1 Referrals will be made through GPs and appropriate community referrers (such as Community Pharmacy and Healthcare advisors trained to offer Community Health Checks) in County Durham and Darlington to the Weight-Less Scheme management hub.

3.6.2 The Weigh-Less Scheme central hub will receive all referrals and it will be the patient's responsibility to register with the hub by telephone or email to discuss appropriate provision. The central weight management hub will confirm the referral acceptance and send approval information to the patient along with details of the chosen provider.

3.6.3 Patients agree for the weigh-less hub to be provided with data regarding weight measurement at 6 months from registration. Data will refer to individuals who return for a free weight measurement at 6 months and for those who may still be engaging with the provider.

3.7 Discharge processes

3.7.1 On completion of the 12 week NHS funded Weigh-Less Scheme patients will be advised of the options available to them as detailed in section 3.1.8

3.8 Response time and prioritisation

3.8.1 All patients will be prioritised by date of referral received into the Weigh-Less Scheme Hub, unless a specific request is received from a GP/community referrer that they would like a patient to be considered priority access and the reason why.

4. Other

4.1 Self-Care and Patient and Carer Information

4.1.1 If patient counselling is poor and patients do not have adequate time or information, failure to achieve their target weight or loose less than 5% of their original weight may be increased along with high drop-out rates.

4.1.2 Good communication between the service provider, healthcare professionals and patients is essential. Face-to-face communication should be supported by evidence-based written information tailored to the patient's needs.

4.1.3 Treatment and care, and the information patients are given about it, should be culturally appropriate. It should also be accessible to people with additional needs such as physical, sensory or learning disabilities, and to people who do not speak or read English.

4.1.4 The service provider will provide suitable and acceptable information about its service in languages and formats relevant to its service population and which accords with the disability discrimination Act 1995 and the Race Relations Act 1976 (amended).

4.1.5 The service provider will make the following information available to individuals:

- Service description
- How to access the service
- How to make a complaint

4.1.6 The service provider will also:

- have available other services information leaflets e.g. Generic Health Improvement Opportunities
- have available other services information leaflets appropriate to the pathway e.g. Exercise on Referral Schemes

5. Quality Requirements

	Indicator	*Threshold*	*Method of Measurement*	*Consequence of Breach*
KPI 1	Number of completed programmes, i.e. number who attend at least 10 out of 12 sessions	50% of referrals to complete	Monthly monitoring reports produced and sent to Weigh-Less Hub for analysis	Service review and action plan

KPI 2	% body weight loss at 12 weeks	≥5% body weight loss for all patients completing the programme	Monthly monitoring reports produced and sent to Weigh-Less Hub for analysis	Service review and action plan
KPI 3	Outcomes of individuals finishing and completing the programme	Data is supplied to the Weigh-Less Hub within 5 months from initial registration	Monthly monitoring reports produced and sent to Weigh-Less Hub for analysis	Service review and action plan
KPI 4	Individuals attending 6 months weigh in Free of Charge	20% of individuals attend and weight is recorded	Monthly monitoring reports produced and sent to Weigh-Less Hub for analysis	Service review and action plan
KPI 5	Patient satisfaction	≥80% of respondents to the service user experience survey answered “satisfied” or “very satisfied” to questions 1, 2 and 3	Service user experience survey	Service review and action plan
KPI 6	Patient knowledge and behaviour	≥80% of respondents to the service user experience survey answered “yes” to questions 4 and 5	Service user experience survey	Service review and action plan
KPI 7	The minimum dataset (MDS)	MDS supplied to Weigh-Less Hub on a monthly basis	Monthly monitoring reports produced and sent to Weigh-Less Hub for analysis	Service review and action plan

6. Activity

6.1 Activity Plan / Activity Management Plan

6.1.1 The provider will produce and maintain a valid up-to-date register of patients being treated as part of the service which forms part of the MDS. This register will be electronic, contemporaneous and provided to the commissioner on a monthly basis using an nhs.net to nhs.net email. The data required is detailed in Module B, Section 5, Part 3 of this document.

6.1.2 The commissioner of this service will provide the service provider with an nhs.net email account prior to the service commencement.

6.1.3 The MDS will also be used to validate invoices received from the provider which will be paid monthly. This is detailed in Module B, Section 5, Part 3 of this document.

6.1.4 To ensure all patients identified as suitable for this service are able to receive a full twelve week programme the provider should not accept any new referrals to the service as part of this contract thirteen weeks prior to the contract end date, unless the patient is able to begin a programme exactly twelve weeks prior to the end.

6.1.5 Any referrals received after this date should be returned to the referrer with an explanation that the contract is ending. The referrer should refer these patients to existing community services.

6.1.6 The service provider is expected to work with the service commissioner to deliver a communications plan to ensure that all GPs and appropriate community referrers within the relevant area are aware of the service including the start date for receiving referrals, the date that the pilot service will no longer accept new referrals, and the date that the pilot service is ending.

6.1.7 As part of this communications plan, sixteen weeks before the end of the contract the provider is expected to ensure all GPs and appropriate community referrers within the relevant area are aware/reminded of the date that the service will no longer accept new referrals and the date that the pilot service is ending.

6.2 Capacity Review

6.2.1 The Commissioner and the Provider shall each monitor and manage activity and referrals for the Services in accordance with Schedule 3 (*Managing Activity and Referrals, Care and Resource Utilisation Techniques*).

6.2.2 The provider should ensure sufficient capacity to meet agreed expected levels of activity. The commissioner and provider will jointly review actual levels of service demand and the commissioner has the right to call a capacity review should activity levels exceed expected levels of demand.

7. Prices and Costs

7.1 Price

7.1.1 The amount paid will be per patient registered with the provider for a 12 week course. Payment will be made in arrears on receipt of an invoice.

7.1.2 The provider will invoice the commissioner monthly in arrears (requirements detailed in Module B, Section 5, Part 3 items 1.1 and 1.2).

7.1.3 The provider will deliver the service within the agreed financial budget detailed below.

7.1.4 The amount paid includes the cost of one follow up appointment to check the progress of the patient.

7.1.5 The commissioner of this service will not pay for patients who fail to attend the initial appointment with the provider.

7.1.6 The amount paid includes all operating costs including any interpretation services required for sensory impaired patients.

7.1.7 Patients who choose to self-refer into this service must do so through a private arrangement with the provider. Any arrangement made between a self-referring patient and the provider is not covered by the terms and conditions set out within this contract.

7.1.8 The cost for self-referring patients will not be paid by the commissioner of this service and therefore the provider should not invoice the commissioner for these patients.

Basis of Contract	Unit of Measurement	Price	Thresholds	Expected Annual Contract Value
Non-Tariff Price (cost per case	Where the patient registers for one community weight management programme through the NHS funded Weigh-Less Scheme (12 consecutive weeks) and one progress check six months following initial registration.	Tariff per 12 week course is expected to be in the region of 48.00 – 60.00 per 12 week course		
Total				

Appendix 8: Exclusion criteria to reduce inequalities

Reducing inequalities is an overarching objective of most public health organisations. Reducing inequalities in opportunities and access to weight management was, therefore, a key objective outlined in the service specification. To support this objective further exclusions, to encourage those with the greatest need, included:

1. Patients who have accessed the service within the previous 12 months
    - To ensure the maximum number of individuals have the opportunity to gain the knowledge and behavioural habits to support ongoing weight management.
2. Patients who have paid to attend a weight loss programmes within the previous 12 weeks
    - This exclusion was design to ensure individuals who were currently able to self-fund weight management programme wouldn't simply switch to publicly funded access.
3. Patients currently participating in the local exercise on referral scheme.
    - The local exercise on referral scheme was one of the current weight management services available. It was design for more complex cases and, thus, it was decided that patients should only attempt one intervention at a time.

Appendix 9: The programme leaflet

What next...?

Step 1:
Telephone Weigh-Less Scheme Hub to register

Step 2:
Choose which group suits you best from a range of venues and times

Step 3:
We send you the information you need. All you have to do is attend your chosen group

Weigh-Less Scheme Hub
Tel: 0191 372 9158
Monday to Friday
Email: jparnaby-gcsx@durham.gcsx.gov.uk

Individuals registered with the Weigh-Less Scheme can take advantage of the following special offer following their slimming on referral programme.

fit4life
4 steps to fitness

step 1
Set your goals
1 x free 1:1 session

step 2
Guided introduction to fitness
3 x free 1:1 sessions

step 3
Supported 6 week fitness programme
only £30.00

step 4
Sustainable fitness membership*
Includes 1 month free fitness

*Terms and Conditions apply

Slimming World

Darlington Borough Council · Durham County Council · NHS County Durham and Darlington

Patient leaflet - March 2012

change 4 Life

NHS County Durham and Darlington

Slimming on referral for County Durham and Darlington

weigh-less scheme

weigh-less scheme

Healthy food and physical activity are essential to sustaining a healthy weight, however all too often, other priorities can get in the way.

Eating healthy and being more active can reduce your risk of serious illness and can be a great way of lifting your mood as well as making you look and feel great.

What is the Weigh-Less Scheme?

- Free 12 Week Slimming on Referral Service
- Support to kick start a more healthy lifestyle
- Support to improve your health and wellbeing

Who is the service for?

- Adults aged 18 years or over
- Registered with a GP in County Durham or Darlington
- Have a BMI of 30-35
- Must be motivated to reaching and maintaining a healthy weight
- Willing to be contacted by the Weigh-Less Scheme to review progress at 6 month and 12 month intervals

Planning to change?

Research shows that people who plan changes to their eating and activity habits are much more likely to lose weight and keep it off than those who look for a "quick fix" solution...

It takes time to break old habits and learn new skills, so you shouldn't feel disheartened if you are not successful all the time.

Increasing your physical activity and making changes to your diet can help to sustain your weight loss.

The change4Life website is full of top tips to support you with ideas such as Snack Swaps and avoiding grazing in front of the TV.

Visit www.nhs.uk/change4Life
or call 0300 123 4567

What can you expect from the service?

- 1 hour (approx) group sessions
- Trained group leader
- Healthy eating goals
- Like-minded individuals
- Support and advice about diet, physical activity and behaviour changes

What do we expect from you?

The Weigh-Less Scheme is designed to help you to lose 5-10% of your bodyweight. The Weigh-Less Scheme will support you with information and strategies to help you maintain a healthy weight but this will take some commitment from you

It is important that you:

- Are committed to achieving and maintaining a healthy weight.
- Are able to regularly attend the 12 week programme.
- Have not attended a commercial weight management service in the last 12 weeks.
- Are willing to take part in follow up reviews relating to your weight loss and the service provided.

It is your responsibility to advise your programme leader of any current medical conditions and medication at your first session and any changes that may occur.

Appendix 10: Details of the data collected by stage of the programme

Referral

Variable	Description
Patient details	
Date of Referral	Date that the individual's referral was made (DD/MM/YYYY)
Name	Forename(s) and Surname name . (NOTE: This information was not provided for this analysis)
Age and DOB	Date of birth (DD/MM/YYYY)
Gender	☐ Male ☐ Female
Ethnicity	☐ White (English/Welsh/Scottish/Northern Irish/British/Irish/Gypsy or Irish Traveller) ☐ Mixed/multiple ethnic groups (White and Black Caribbean / White and Black African / White and Asian) ☐ Asian/Asian British (Indian, Pakistani, Bangladeshi, Chinese) ☐ Black/African/Caribbean/ Black British ☐ Other ethnic group (please state)
Address	Home contact address for patient. (NOTE: This information was not provided for this analysis)
Postcode	Home postcode of patient. (NOTE: Postcode not provide for analysis only measure of deprivation)
Telephone	Telephone contact for patient. (NOTE: This information was not provided for this analysis)
Email	Email contact for patient. (NOTE: This information was not provided for this analysis)
Referrer details	
Name	Title, forename(s) and surname of the individual who made the referral. (NOTE: This information was not provided for this analysis)
Address	Address of the individual who made the referral. (NOTE: Only the organisation name was provided for analysis. The full address was not provided.)
Postcode	Postcode of the individual who made the referral. (NOTE: This information was not provided for this analysis)
Telephone	Telephone contact of the individual who made the referral. (NOTE: This information was not provided for this analysis)
Email	Postcode of the individual who made the referral. (NOTE: This information was not provided for this analysis)
Patient health details	
Reason for Referral:	☐ Patient request (self-referral) ☐ Health professional referral ☐ Underlying health condition ☐ Weight loss required for health intervention
Co-morbidities	☐ >20% CVD risk ☐ Hypertension ☐ Diabetes ☐ Stroke ☐ Asthma/COPD ☐ Joint problems

	☐ Heart disease ☐ Depression ☐ Stress/anxiety ☐ Arthritis ☐ Musculoskeletal conditions ☐ Back problems ☐ Hyperlipidaemia
Weight	Weight measured in kilograms (kg)
Height	Height in metres (m)
BMI	Body Mass Index
Waist	Waist measurement in centimetres (cm)
Blood Pressure	Systolic blood pressure / Diastolic blood pressure
Alcohol intake	Alcohol consumption (estimated units per week)
Smoking status	Smoking status (estimated cigarettes per day)
Disability Status	Registered as disabled (Y/N)

Registration

Variable	**Description**
Date of registration	The date the individual called to register for the weight management service (DD/MM/YYYY)
Physical activity	Measure of physical activity using the Stanford 7 Day Recall *"On average how many hours per week do you spend sleeping?"* *"On average how many hours per week do you spend engaged in moderate physical activities?"* *"On average how many hours per week do you spend engaged in hard physical activities?"* *"On average how many hours per week do you spend engaged in very hard physical activities?"* [NOTE: MET levels are assigned to each class of activities, sleep = 1 MET; light = 1.5 METs; moderate = 4 METs; hard = 6 METs and very hard = 10 METs. The time spent in each activity for the past 7 days are multiplied by their respective MET values. An estimate of the total kilocalories of energy expenditure per day is calculated.]
Diet	Measure of self-perception of diet using the following questions: "*Please could you indicate, on a scale of 0-10, how true the following statements are. Where 0 = not at all true and 10 = completely true."* ☐ I eat well balanced food ☐ I avoid cholesterol rich food ☐ I actively try to eat little fat ☐ I choose low fat meats ☐ I don't eat fast food ☐ I am aware of the calories in my food ☐ I choose low fat dairy products ☐ I always remove visible fat from my food

	☐ I drink sugar free soft drinks ☐ When I eat cake or chocolate I only have small portions
Marital status	*"What is your current marital or same-sex civil partnership status?"* ☐ Single ☐ Cohabiting ☐ Married ☐ Separated ☐ Divorced ☐ Widowed
Presence of children	*"How many children do you have?"* - Number of children
Education	*"What is your highest educational qualification(s)?"* ☐ No qualifications ☐ 1 or more 'O' level passes/CSE/GCSE of any grades or NVQ level 1/Foundation GNVQ or equivalent ☐ 5 or more 'O' level passes/CSEs (grade 1)/GCSEs (grades A-C) or School Certificate or 1 or more 'A' levels/AS levels or NVQ level 2/Intermediate GNVQ or equivalent. ☐ 2 or more 'A' levels/4 or more AS levels or Higher School Certificate or NVQ level 3/Advanced GNVQ or equivalent ☐ First degree/Higher degree or NVQ levels 4 and 5 or Qualified teacher/nurse or equivalent or higher
Employment	*"Are you?"* ☐ Employed in paid work? ☐ Employed in non-paid work? ☐ Unemployed and actively looking for work? ☐ Unemployed and not working for work? ☐ Full time student? ☐ None of the above/prefer not to answer *"How many hour a week (both paid and unpaid) do you usually work?"* ☐ 15 or less ☐ 16 - 30 ☐ 31 - 48 ☐ 49 or more *"If unemployed, how long have you been unemployed (months)?"*
Income	*"What is your total household income from all sources over the last 12 months?*"* ☐ £0-9,999 ☐ £10,000-19,999 ☐ £20,000-29,999 ☐ £30,000-39,999 ☐ £40,000-49,999 ☐ £50,000-35,999 ☐ £60,000-69,999 ☐ £70,000+ * Count income from every person included in the household. Include: - All earnings (include overtime, tips, bonuses, self-employment) - All pensions

	- All student grants and bursaries (but not loans) - All benefits and tax credits (such as child benefit, income support or pension credit) - All interest from savings or investments - All rent from property (after expenses) - Other income (such as maintenance or grants) Do not deduct: - Taxes, National Insurance contributions, Health Insurance Payments, Superannuation payments
Housing tenure	*"What accommodation do you currently live in?"* ☐ Owner occupied- owned outright ☐ Owner occupied- with a mortgage or loan ☐ Shared ownership- part rent and part mortgage *(plus landlord, see below)* ☐ Rented *(plus landlord, see below)* ☐ Live here rent free *(plus landlord, see below)* ☐ Squatting *"Who is you landlord?"* ☐ The local authority/council/New Town Housing Development ☐ A housing association or co-operative or charitable trust ☐ Private landlord or letting agent ☐ Employer of a household member ☐ Relative/friend of household member ☐ Other
Local area	Measure of physical activity and healthy eating opportunities in the local area based on average score from the following questions: "*Thinking about your local area please indicate whether the following statements are: Not at all true (score=0) Partly true (score=1) Mostly true (score=2) Completely true (score=3)*" – The amount and speed of the traffic is not a problem – There are few take-away and/or fast food outlets – Crime is a problem in this area – There is lots of green space such as parks, gardens and children's play areas – It is easy and pleasant to walk and/or cycle around the area – There are good public transport links for where I want to go – There are good leisure facilities for people like me – There are plenty of places to get healthy food such as fresh fruit and vegetables – It is a good place to live
Personality	Measure of personality using the Big 5 measure. *"Please could you indicate, on a scale of 0-10, how true the following statements are. Where 0 = completely disagree and 10 = completely agree. I see myself as someone who…"* …is reserved …is generally trusting …tends to be lazy …is relaxed/handles stress well …has few artistic interests

	…is outgoing sociable …tends to find fault with others …does a thorough job …gets nervous easily …has an active imagination Scores from questions 1, 3, 4, 5 and 7 are reversed. These are added to the remaining scores to create totals for each category as follows: Extraversion: 1R, 6 Agreeableness: 2, 7R Conscientiousness: 3R, 8 Neuroticism: 4R, 9 Openness: 5R, 10 (Big Five Inventory Questions, adapted from Rammstedt and John, 2007)

During the weight management service

Variable	**Description**
Start date	Date that the individual first attends the service (DD/MM/YYYY)
Weight at week 1	Weight in kg at week 1
Weight at week 2	Weight in kg at week 2
Weight at week 3	Weight in kg at week 3
Weight at week 4	Weight in kg at week 4
Weight at week 5	Weight in kg at week 5
Weight at week 6	Weight in kg at week 6
Weight at week 7	Weight in kg at week 7
Weight at week 8	Weight in kg at week 8
Weight at week 9	Weight in kg at week 9
Weight at week 10	Weight in kg at week 10
Weight at week 11	Weight in kg at week 11
Weight at week 12	Weight in kg at week 12

Appendix 11: Service user experience survey

change 4 life
Eat well Move more Live longer

Ref:

slimming world
satisfaction survey

Your feedback is valuable to us. All responses are treated in the strictest confidence and are used to make improvements to the Weigh-Less Scheme.

1. overall how satisfied are you with the programme?

☐ Very Dissatisfied☹ ☐ Dissatisfied ☐ Satisfied ☐ Very Satisfied ☺

2. overall how satisfied are you with the venue?

☐ Very Dissatisfied☹ ☐ Dissatisfied ☐ Satisfied ☐ Very Satisfied ☺

	Strongly disagree			Strongly agree
The location of the venue was convenient for me	☐	☐	☐	☐
The days/times of the classes were convenient for me	☐	☐	☐	☐
The venue and facilities were suitable for the activities undertaken	☐	☐	☐	☐
The venue had good access	☐	☐	☐	☐

3. overall how satisfied are you with the content?

☐ Very Dissatisfied☹ ☐ Dissatisfied ☐ Satisfied ☐ Very Satisfied ☺

	Strongly disagree			Strongly agree
The information provided was understandable	☐	☐	☐	☐
The information available was flexible to my lifestyle and needs	☐	☐	☐	☐
The information helped me achieve my weight-loss goal	☐	☐	☐	☐
The programme was enjoyable	☐	☐	☐	☐

4. overall how satisfied are you with the consultant?

☐ Very Dissatisfied☹ ☐ Dissatisfied ☐ Satisfied ☐ Very Satisfied ☺

	Strongly disagree			Strongly agree
The consultant was friendly and welcoming	☐	☐	☐	☐
The consultant demonstrated good knowledge of weight-loss	☐	☐	☐	☐
The consultant offered help and support when needed	☐	☐	☐	☐
The consultant discussed next steps for after the programme	☐	☐	☐	☐

5. as a result of the programme do you have the knowledge to...

...eat more healthily?	☐ No☹	☐ Yes ☺
...be more physically active?	☐ No☹	☐ Yes ☺
...lead a healthy lifestyle?	☐ No☹	☐ Yes ☺

6. as a result of the programme you...

...eat more healthily?	☐ No☹	☐ Yes ☺
...are more physically active?	☐ No☹	☐ Yes ☺
...lead a healthier lifestyle?	☐ No☹	☐ Yes ☺

7. the following helped you to eat more healthily…

	Strongly disagree			Strongly agree
…the information provided	☐	☐	☐	☐
…the consultant	☐	☐	☐	☐
…group members	☐	☐	☐	☐

Other (please state)
………

8. the following helped you to be more physically active…

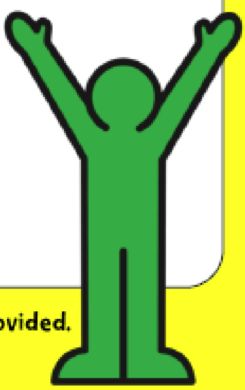
	Strongly disagree			Strongly agree
…the information provided	☐	☐	☐	☐
…the consultant	☐	☐	☐	☐
…group members	☐	☐	☐	☐

Other (please state)
………

9. as a result of the programme you…

	Strongly disagree			Strongly agree
…have more self confidence	☐	☐	☐	☐
… are more outgoing and sociable	☐	☐	☐	☐
…are confident that you can continue to lead a healthy active lifestyle	☐	☐	☐	☐

Please use the space below to provide any further comments about the programme, including both aspects you liked and disliked and any thoughts for improvements.



Thank you for completing this survey. Please return in the free post envelope provided.

Appendix 12: The Procurement Process

Research

Between April and September 2011 I conducted extensive research in support the development of the service specification.

The service specification is a document that contains a description of the requirements of the service. It sets out how the service will be delivered and how the quality of service delivery will be measured (Key Performance Indicators) ensuring an effective service is commissioned with a provider that can be held to account if outcomes are not achieved.

The research consisted of information gathered from two main sources. The first was a review of the academic literature including evaluations of weight management interventions. The second was a review of the documentation of other NHS organisations commissioning weight management services and contacting these organisations to discuss key learning points and best practice.

My broad conclusions were that there was a multitude of existing potential providers suitable for providing weight management services, thus, negating the need to develop and create a bespoke service from scratch. Further, these services, whilst all suffering from high attrition rates did seem, on the whole, to deliver the level of weight reduction NICE guidance considered to produce significantly increased health outcomes.[77] Expected costs were more difficult to obtain, however, from the limited information we expected costs anywhere between £45 and £150, per individual, per 12 week programme.

[77] NICE guidance recommends weight reduction of 5-10% of initial body weight over a 12 week programme. Full guidance can be found at: http://www.nice.org.uk/guidance/cg43

Speaking directly to other NHS professional was highly advantageous for supporting decisions on particular details of the service specification such as the Key Performance Indictors and contracting arrangements.

Specification development

Based on the research the team were able to finalise the service specification. The full service specification is available in Appendix 7.

Procurement

Several contracting options were considered. An Any Qualified Provider (AQP)[78] contracting arrangement was initially discussed, however, due to limited funds and the lack of an ability to cap demand this arrangement was considered unfeasible. Due to geographical variations in need and the desire to encourage a wide range of bidders the decision was made to divide County Durham and Darlington into three distinct areas and to offer three contracts. Providers could bid for one, two or all three areas.

Tendering process

With the service specification completed the final task before the service could be advertised to potential bidders was to design the evaluative process. The key tasks were to develop the questions for bidders to answer and to develop the scoring methodology.

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[78] Any Qualified Provider is a contracting arrangement in which all providers meeting the qualification criteria are awarded a contract and are subsequently available for patients to select from.

Documentation of the evaluation questions and scoring methodology can be found in Appendix 13. In 2011 this document and the service specification were advertised to potential bidders through the appropriate NHS procurement channels.

Evaluation of bids

The evaluative process took place in December 2011. Due to the contracting arrangements a large number of bids were received. The evaluation panel, include myself, met for a full week to review and score the bids received documenting details our rationale for the scores. Details of bidders and scores are confidential.

Contract award

All bidders were provided with feedback of their scores and the score of the winning bidder. An organisation called Slimming World bid on all three areas and scored highest in each, therefore, winning all three contracts.

Service mobilisation

Several mobilisation activities occurred between contract award and service delivery. These include:

1. Due to the universal access to participation the consultants would potentially be working with adults considered "vulnerable". To meet NHS requirements all Slimming World consultants (the group leaders) had to be CRB[79] (now called DBS) checked.

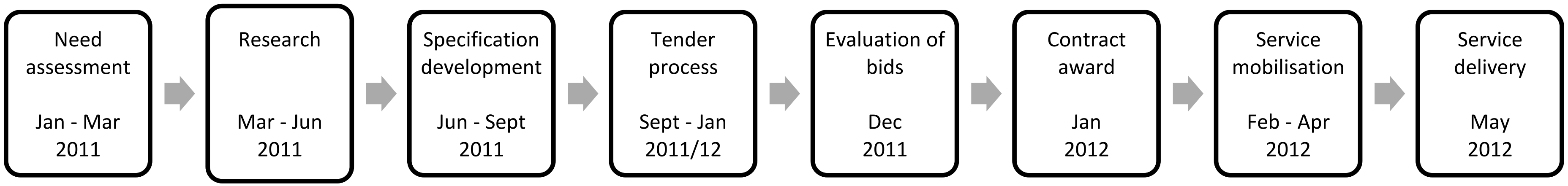
[79] Criminal Records Bureau check

2. Further, an administrative support system had to be created to manage the full system. It was decided that the local authority would host an administrative support team which would manage patients, referrers and the Slimming World, ensuring uninterrupted smooth operation.
3. A database had to be developed to collate information from various points in the service. An external company was approach to design and develop it, however, both the initial cost and the cost of future alterations and amendments was considered too high. Developing the database also for flexibility and internal control of its design and future capabilities.

Service delivery

The first referral was made on 14th May 2012.

Activity Timeline for the Commissioning of the Weight Management Programme



Appendix 13: Evaluation questions and scoring methodology

ITT Question Number	Category	Max Score Available	Max % Weighting	Overall Weighting
Section 1 – Service Model				
SM1.1	Service Model	20	12%	35%
SM1.2	Service Model	20	10%	
SM1.3	Service Model	20	8%	
SM1.4	Service Model	20	5%	
Section 2 – Finance				
	Affordability	Pass/Fail		30%
	Costs per Completed Pathway	30%	30%	
Section 3 – Mobilisation				
M3.1	Mobilisation	20	10%	25%
M3.2	Mobilisation	20	5%	
M3.3	Mobilisation	20	10%	
Section 4 – Equipment & Premises				
EP4.1	Equipment & Premises	20	3%	5%
EP4.2	Equipment & Premises	20	2%	
Section 5 – Workforce				
W5.1	Workforce	20	5%	5%
W5.2	Workforce	Pass/Fail		
Total:				**100%**

Section 1 – Service Model – 35%

[SM1.1] Service Model - 12%
Please outline your service delivery model and how it meets the multi-component requirements of the Community Weight Management Service Specification (Section 2, 3 and 4 of the Service Specification) Your response should include, but not be limited to; • Detail of the service users journey through the entire service model, from the initial contact with the service to the 6 month follow-up. • Detail on how the service meets the needs of the specific service user. • Detail how the service meets the needs of different age ranges and language, literacy and disability needs. • Resources available to the service user and how you will ensure access to them • Proposed validated measurement tools for assessing service-user outcomes including how the tools are audited/checked for accuracy. • Healthy eating strategies • Motivational techniques • How you enable access to or promote physical activity. **Maximum word count 2000.**

[SM1.2] Service Model – 10%
Please outline how your proposed service model (outlined in question SM1.1) will achieve **each** of the quality requirements and the evidence base (Section 1, 2, 5 and 6 of the Service Specification). Your response should include, but not be limited to; • Mechanisms and capacity for monitoring and managing achievement of the contract. • Proposals for mitigating risk of non-achievement for individuals; • Evidence of successful weight management delivery in the past. • Reliable research or evaluation that will support your service model to demonstrate how it meets the evidence base and/or how it has shown to be effective, including any independent evaluation. • Evidence of how the service meets NICE obesity guidance **Maximum word count 1500.**

[SM1.3] Service Model – 8%
Please provide and outline your plans to mitigate and manage risk in the following scenarios (Section 3 of the Service Specification). • Safeguarding and vulnerable adults issues. • Continuity of service in the event of exceptional circumstances, such as adverse weather conditions, high level of staff absence. • IT disruption or failure. • Business continuity plans. **Maximum word count 1000**.

[SM1.4] Service Model – 5%
Please outline how your IM&T approach will meet the reporting requirements as outlined in section 5 and 6 of the specification and in your proposed service model. (Section 5 and 6 of Service Specification). Your response should include, but not be limited to; • Data collection tools • Data storage facilities • Data sharing and extraction processes • Proposed reporting arrangements • Record management processes, including Information Governance and Data Protection processes **Maximum word count 800.**

Section 2 – Finance – 30%

Completion of the financial model template

1. Evaluation of bidder's ability to meet the affordability envelope

Bids will be evaluated against the annual financial affordability limit for this procurement and **any bid in excess of this limit will be excluded from the process at this stage**. In this event, further evaluation of the ITT will not be undertaken and the potential Bidder will not be taken any further in the evaluation process.

The affordability threshold for this service is £305,000 further divided into Darlington £40,000, North Durham £120,000 and South Durham £140,000. Any bids submitted with a price above the affordability threshold for each area, or, if bidding for all 3 lots, above the affordability threshold in total will be disqualified from this procurement.

2. Evaluation of bidders costs per completed pathway

The evaluation methodology in relation to costs per completed pathway will be attributed a score as detailed in the following table:

Cost per Pathway	Score Achieved (Max score 30%)
Lowest Cost	30%
Within 5% of Lowest Cost	27%
Within 10% of Lowest Cost	24%
Within 15% of Lowest Cost	21%
Within 20% of Lowest Cost	18%
Within 25% of Lowest Cost	15%
Within 30% of Lowest Cost	12%
Within 35% of Lowest Cost	9%
Within 40% of Lowest Cost	6%
More than 40% above Lowest Cost	0%

Section 3 – Mobilisation – 25%

[M3.1] Mobilisation – 10%
Please detail how you will ensure that the service venues and equipment are in place for service commencement (Section 2, 3 and 4 of Service Specification). Your response should include, but not limited to; • A proposed project timetable for identifying, assessing and acquiring premises and

equipment, to include a service live date.
- Details of the process for identifying, assessing and acquiring premises and equipment.
- Identification of any risks and mitigation to setting up the service.

Maximum word count 1500.

[M3.2] Mobilisation – 5%

Please outline your mobilisation plan in respect of stakeholder engagement (Section 2, 3 and 4 of Service Specification).

Your response should include, but not limited to;

- Marketing of service to stakeholders
- Proposed plans and processes for informing stakeholders in conjunction with the commissioner and engaging them in the establishment and promotion of the service;
- Proposed plans for engaging service-users in the service
- Any marketing and promotional material which is given to the service users and the stakeholders

Maximum word count 800.

[M3.3] Mobilisation – 10%

Please outline your mobilisation plan in respect of recruitment and training of staff for the start of the service (Section 3 of Service Specification).

Your response should include, but not limited to;

- Details of training courses
- Recruitment methods
- Pre-Employment checks

Maximum word count 1500.

Section 4 – Equipment & Premises – 5%

[EP4.1] Equipment & Premises – 3%

Please outline details of all the premises that you intend to use for the delivery of the service and how they will be used, ensuring equity of provision and accessibility for all localities. (Section 1, 2 and 3 of Service Specification)

Your response should also include, but not limited to;

- Geographical and spread across the communities of Darlington, South and North Durham, taking into consideration the geographical differences in each of the localities
- Examples of existing and proposed premises
- Hours of availability, including any flexibilities and extent of coverage that will be offered
- Assessment of public transport links
- Accessibility for all service users, including deprived communities, BME groups those

with sensory and physical disabilities • Dignity and respect for all service users **Maximum word count 750**
[EP4.2] Equipment & Premises – 2%
Please outline details of all the equipment that will be used in order to deliver the service outlining how this supports the service model (Section 2,3,4,5 and 6 of Service Specification). Your response should also include, but not limited to; • Plans for maintenance of equipment • Health & Safety considerations • Risk Assessments **Maximum word count 500.**

Section 5 – Workforce – 5%

[W5.1] Workforce – 5%			
Please outline your proposed staffing model for the period of the contract, demonstrating overall fit with the quality requirements of the service. (Section 2, 5 and 6 of Service Specification). Your response should include, but not limited to: • Operational management structure; • Roles and responsibilities; • Details of how you will ensure that staff are competent, confident and effective in delivering the intervention • Performance management • Accountability and Reporting arrangements **Maximum word count 800**			
[W5.2] Workforce (Pass/Fail)			
The PCT require all staff directly providing this service to have a Criminal Records Bureau (CRB) check. (Section 2.7.2 of Service Specification). Do all staff who will be providing this service directly have a CRB check?			
YES		**NO**	
If your answer is **NO** please detail your implementation plan to comply with this requirement.			

Appendix 14: Registers for the service
(n=1,764)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	1.30	0.50	0.01	0.32	2.27
Demographics					
Male	-0.40	0.09	0.00	-0.58	-0.21
Age	0.01	0.01	0.69	-0.02	0.03
Age squared	0.00	0.00	0.85	0.00	0.00
White (ethnicity)	-0.49	0.37	0.18	-1.21	0.23
Indices of deprivation	0.01	0.01	0.27	-0.01	0.04
Weight factors					
BMI (initial)	0.00	0.01	0.66	-0.01	0.01
Aspect of the programme					
Self-referred	0.05	0.06	0.45	-0.08	0.18
Health behaviours					
Smokes	-0.29	0.09	0.00	-0.46	-0.12
Excess alcohol consumption	-0.07	0.11	0.52	-0.28	0.14
Physical health					
Disabled	0.01	0.15	0.96	-0.29	0.31
Cardiovascular disease	-0.13	0.12	0.29	-0.36	0.11
Mobility problems	0.08	0.08	0.36	-0.09	0.24
Diabetes	-0.14	0.10	0.16	-0.35	0.06
Hypertension	-0.06	0.09	0.46	-0.23	0.11
Mental health					
Depression	-0.11	0.10	0.27	-0.31	0.09
Stress	0.06	0.13	0.64	-0.19	0.31

Appendix 15: Started the service
(n=1,764)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	1.23	0.83	0.14	-0.40	2.86
Demographics					
Male	-0.20	0.15	0.18	-0.50	0.09
Age	0.04	0.02	0.06	0.00	0.07
Age squared	0.00	0.00	0.14	0.00	0.00
White (ethnicity)	-0.81	0.59	0.17	-1.96	0.35
Indices of deprivation	-0.02	0.02	0.26	-0.06	0.02
Partner	0.12	0.09	0.18	-0.06	0.30
Presence of children	-0.09	0.12	0.47	-0.33	0.15
Employed	0.11	0.10	0.28	-0.09	0.30
Degree level education	0.28	0.13	0.04	0.02	0.54
Perception of local area	0.01	0.00	0.02	0.00	0.01
Weight factors					
BMI (initial)	0.01	0.01	0.61	-0.02	0.03
Aspect of the programme					
Self-referred	0.19	0.09	0.04	0.01	0.37
Days (referral to registration)	-0.03	0.00	0.00	-0.03	-0.02
Health behaviours					
Smokes	-0.17	0.12	0.17	-0.41	0.07
Excess alcohol consumption	-0.09	0.15	0.55	-0.38	0.21
Perception of diet	0.00	0.00	0.10	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.65	0.00	0.00
Physical health					
Disabled	0.38	0.25	0.14	-0.12	0.87
Cardiovascular disease	-0.09	0.17	0.59	-0.43	0.24
Mobility problems	0.18	0.11	0.13	-0.05	0.40
Diabetes	-0.08	0.15	0.60	-0.37	0.21
Hypertension	0.00	0.12	0.97	-0.23	0.24
Mental health					
Depression	0.06	0.15	0.69	-0.23	0.34
Stress	-0.28	0.16	0.08	-0.59	0.04
Personality					
Openness	0.00	0.00	0.98	0.00	0.00
Neuroticism	0.00	0.00	0.56	0.00	0.00
Conscientiousness	0.00	0.00	0.45	-0.01	0.00
Agreeableness	-0.01	0.00	0.01	-0.01	0.00
Extroversion	0.00	0.00	0.75	0.00	0.00

Appendix 16: Table (A) Percentage weight change of individuals engaged at week 10
OLS Regression including the Inverse Mills Ratio as a regressor (n=1,099)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	-5.43	3.00	0.07	-11.31	0.46
Inverse Mills Ratio (λ)	3.85	2.46	0.12	-0.97	8.68
	Demographics				
Male	-0.17	0.31	0.59	-0.77	0.44
Age	-0.04	0.04	0.35	-0.13	0.05
Age squared	0.00	0.00	0.39	0.00	0.00
White (ethnicity)	-1.42	0.74	0.06	-2.87	0.04
Deprivation score	-0.06	0.04	0.10	-0.13	0.01
Partner	-0.04	0.19	0.83	-0.42	0.34
Presence of Children	-0.25	0.41	0.54	-1.06	0.56
Employed	0.35	0.19	0.06	-0.02	0.72
Degree level education	-0.63	0.21	0.00	-1.05	-0.21
Perception of local area	0.00	0.01	0.45	-0.01	0.02
	Weight factors				
BMI (initial)	0.07	0.02	0.00	0.02	0.12
Weight change (kg) week 2	0.46	0.12	0.00	0.23	0.69
	Aspect of the programme				
Self-referred	-0.36	0.16	0.03	-0.68	-0.04
Days (referral to registration)	0.00	0.01	0.60	-0.02	0.01
Days (registration to start)	-0.04	0.02	0.02	-0.07	-0.01
Consistent attendance	-1.50	0.16	0.00	-1.82	-1.18
	Health behaviours				
Smokes	-1.10	0.44	0.01	-1.96	-0.24
Excess alcohol consumption	0.82	0.31	0.01	0.21	1.42
Perception of diet	0.02	0.01	0.00	0.01	0.04
Energy expenditure (kcal/day)	0.00	0.00	0.42	0.00	0.00
	Physical health				
Disabled	0.37	0.50	0.46	-0.62	1.35
Cardiovascular disease	0.30	0.31	0.35	-0.32	0.91
Mobility problems	0.45	0.23	0.05	0.00	0.91
Diabetes	0.69	0.31	0.03	0.08	1.31
Hypertension	-0.10	0.22	0.66	-0.52	0.33
	Mental health				
Depression	-0.23	0.39	0.56	-1.00	0.55
Stress	-0.05	0.33	0.89	-0.69	0.60
	Personality				
Openness	0.00	0.00	0.73	-0.01	0.01
Neuroticism	0.00	0.00	0.74	-0.01	0.01
Conscientiousness	0.00	0.00	0.47	-0.01	0.01
Agreeableness	0.00	0.00	0.89	-0.01	0.01
Extroversion	-0.01	0.00	0.13	-0.01	0.00

Appendix 16: Table (B) BMI change of individuals engaged at week 10
OLS Regression including the Inverse Mills Ratio as a regressor (n=1099)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	0.92	1.72	0.60	-2.46	4.29
Inverse Mills Ratio (λ)	0.21	1.41	0.88	-2.56	2.98
	Demographics				
Male	-0.23	0.18	0.19	-0.58	0.11
Age	-0.01	0.03	0.66	-0.06	0.04
Age squared	0.00	0.00	0.76	0.00	0.00
White (ethnicity)	-0.57	0.42	0.18	-1.41	0.26
Indices of deprivation	-0.01	0.02	0.50	-0.06	0.03
Partner	-0.04	0.11	0.73	-0.26	0.18
Presence of Children	0.09	0.24	0.72	-0.38	0.55
Employed	0.04	0.11	0.69	-0.17	0.26
Degree level education	-0.11	0.12	0.35	-0.36	0.13
Perception of local area	0.00	0.00	0.34	0.00	0.01
	Weight factors				
BMI (initial)	-0.04	0.01	0.01	-0.06	-0.01
Weight change (kg) week 2	0.22	0.07	0.00	0.09	0.35
	Aspect of the programme				
Self-referred	-0.15	0.09	0.10	-0.33	0.03
Days (referral to registration)	0.00	0.00	0.58	-0.01	0.01
Days (registration to start)	-0.01	0.01	0.20	-0.03	0.01
Consistent attendance	-0.61	0.09	0.00	-0.80	-0.43
	Health behaviours				
Smokes	-0.43	0.25	0.09	-0.92	0.06
Excess alcohol consumption	0.24	0.18	0.18	-0.11	0.59
Perception of diet	0.00	0.00	0.41	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.48	0.00	0.00
	Physical health				
Disabled	-0.22	0.29	0.44	-0.79	0.34
Cardiovascular disease	0.45	0.18	0.01	0.10	0.80
Mobility problems	0.03	0.13	0.80	-0.23	0.29
Diabetes	-0.01	0.18	0.94	-0.37	0.34
Hypertension	0.03	0.12	0.80	-0.21	0.28
	Mental health				
Depression	0.15	0.23	0.50	-0.29	0.59
Stress	-0.12	0.19	0.51	-0.49	0.25
	Personality				
Openness	0.00	0.00	0.79	0.00	0.00
Neuroticism	0.00	0.00	0.36	0.00	0.01
Conscientiousness	0.00	0.00	0.92	-0.01	0.00
Agreeableness	0.00	0.00	0.98	-0.01	0.01
Extroversion	0.00	0.00	0.09	-0.01	0.00

Appendix 16: Table (C) Significant weight loss of individuals engaged at week 10
Maximum Likelihood Estimation including the Inverse Mills Ratio as a regressor (n=1099)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	-2.71	1.41	0.06	-5.47	0.05
Inverse Mills Ratio (λ)	0.86	0.73	0.24	-0.56	2.29
	Demographics				
Male	0.17	0.17	0.31	-0.16	0.50
Age	0.04	0.02	0.08	-0.01	0.09
Age squared	0.00	0.00	0.18	0.00	0.00
White (ethnicity)	0.84	0.46	0.07	-0.07	1.74
Indices of deprivation	-0.03	0.02	0.18	-0.07	0.01
Partner	0.22	0.11	0.05	0.00	0.44
Presence of Children	-0.25	0.14	0.08	-0.52	0.03
Employed	-0.26	0.13	0.04	-0.50	-0.01
Degree level education	0.32	0.15	0.03	0.04	0.61
Perception of local area	0.00	0.00	0.57	0.00	0.01
	Weight factors				
BMI (initial)	-0.05	0.02	0.01	-0.08	-0.01
Weight change (kg) week 2	-0.39	0.11	0.00	-0.61	-0.16
	Aspect of the programme				
Self-referred	0.25	0.11	0.03	0.03	0.47
Days (referral to registration)	0.00	0.00	0.47	0.00	0.01
Days (registration to start)	0.02	0.01	0.02	0.00	0.03
Consistent attendance	0.93	0.28	0.00	0.37	1.49
	Health behaviours				
Smokes	0.24	0.17	0.16	-0.09	0.58
Excess alcohol consumption	-0.33	0.18	0.06	-0.68	0.02
Perception of diet	-0.01	0.00	0.05	-0.01	0.00
Energy expenditure (kcal/day)	0.00	0.00	0.22	0.00	0.00
	Physical health				
Disabled	0.31	0.23	0.18	-0.14	0.75
Cardiovascular disease	-0.08	0.17	0.64	-0.40	0.25
Mobility problems	0.00	0.10	1.00	-0.20	0.20
Diabetes	-0.16	0.15	0.30	-0.45	0.14
Hypertension	0.11	0.12	0.34	-0.12	0.34
	Mental health				
Depression	0.11	0.16	0.50	-0.21	0.42
Stress	-0.24	0.19	0.21	-0.61	0.13
	Personality				
Openness	0.00	0.00	0.57	0.00	0.01
Neuroticism	0.00	0.00	0.68	0.00	0.00
Conscientiousness	0.00	0.00	0.31	0.00	0.01
Agreeableness	0.00	0.00	0.53	0.00	0.01
Extroversion	0.00	0.00	0.06	0.00	0.01

Appendix 16: Table (D) Percentage weight change of individuals engaged at week 12
OLS Regression including the Inverse Mills Ratio as a regressor (n=851)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	-2.38	5.03	0.64	-12.25	7.49
Inverse Mills Ratio (λ)	1.96	3.44	0.57	-4.79	8.71
	Demographics				
Male	-0.13	0.48	0.78	-1.08	0.81
Age	-0.08	0.06	0.16	-0.19	0.03
Age squared	0.00	0.00	0.18	0.00	0.00
White (ethnicity)	-2.35	1.00	0.02	-4.32	-0.38
Indices of deprivation	-0.05	0.05	0.32	-0.14	0.05
Partner	-0.16	0.23	0.48	-0.62	0.29
Presence of Children	-0.09	0.56	0.88	-1.18	1.01
Employed	0.16	0.25	0.51	-0.33	0.65
Degree level education	-0.71	0.28	0.01	-1.26	-0.17
Perception of local area	-0.01	0.01	0.44	-0.02	0.01
	Weight factors				
BMI (initial)	0.09	0.05	0.07	-0.01	0.20
Weight change (kg) week 2	0.62	0.17	0.00	0.29	0.94
	Aspect of the programme				
Self-referred	-0.18	0.24	0.45	-0.65	0.29
Days (referral to registration)	0.00	0.01	0.64	-0.02	0.01
Days (registration to start)	-0.04	0.02	0.14	-0.08	0.01
Consistent attendance	-1.63	0.66	0.01	-2.92	-0.33
	Health behaviours				
Smokes	-0.93	0.57	0.10	-2.05	0.19
Excess alcohol consumption	0.40	0.39	0.31	-0.37	1.17
Perception of diet	0.01	0.01	0.11	0.00	0.03
Energy expenditure (kcal/day)	0.00	0.00	1.00	0.00	0.00
	Physical health				
Disabled	-0.23	0.53	0.67	-1.26	0.81
Cardiovascular disease	0.40	0.53	0.45	-0.63	1.44
Mobility problems	0.20	0.29	0.48	-0.36	0.76
Diabetes	0.93	0.54	0.09	-0.13	1.98
Hypertension	-0.33	0.34	0.34	-0.99	0.34
	Mental health				
Depression	0.13	0.49	0.80	-0.84	1.10
Stress	-0.02	0.46	0.96	-0.92	0.88
	Personality				
Openness	0.00	0.01	0.71	-0.02	0.01
Neuroticism	0.00	0.01	0.55	-0.01	0.01
Conscientiousness	0.00	0.01	0.68	-0.01	0.01
Agreeableness	0.00	0.01	0.87	-0.01	0.01
Extroversion	-0.01	0.00	0.06	-0.02	0.00

Appendix 16: Table (E) BMI change of individuals engaged at week 12

OLS Regression including the Inverse Mills Ratio as a regressor (n=851)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	3.35	1.78	0.06	-0.15	6.86
Inverse Mills Ratio (λ)	-0.81	1.22	0.51	-3.20	1.59
	Demographics				
Male	-0.20	0.17	0.25	-0.53	0.14
Age	-0.03	0.02	0.08	-0.07	0.00
Age squared	0.00	0.00	0.28	0.00	0.00
White (ethnicity)	-0.90	0.36	0.01	-1.60	-0.20
Indices of deprivation	-0.01	0.02	0.54	-0.04	0.02
Partner	-0.05	0.08	0.55	-0.21	0.11
Presence of Children	0.22	0.20	0.27	-0.17	0.61
Employed	0.03	0.09	0.75	-0.15	0.20
Degree level education	-0.25	0.10	0.01	-0.44	-0.06
Perception of local area	0.00	0.00	0.69	-0.01	0.00
	Weight factors				
BMI (initial)	-0.05	0.02	0.00	-0.09	-0.02
Weight change (kg) week 2	0.30	0.06	0.00	0.19	0.42
	Aspect of the programme				
Self-referred	-0.09	0.08	0.29	-0.26	0.08
Days (referral to registration)	0.00	0.00	0.33	-0.01	0.00
Days (registration to start)	0.00	0.01	0.70	-0.02	0.01
Consistent attendance	-0.88	0.23	0.00	-1.34	-0.42
	Health behaviours				
Smokes	-0.13	0.20	0.52	-0.53	0.27
Excess alcohol consumption	0.19	0.14	0.17	-0.08	0.47
Perception of diet	0.00	0.00	0.37	0.00	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.22	0.00	0.00
	Physical health				
Disabled	-0.22	0.19	0.25	-0.58	0.15
Cardiovascular disease	0.02	0.19	0.93	-0.35	0.38
Mobility problems	0.04	0.10	0.68	-0.16	0.24
Diabetes	0.16	0.19	0.41	-0.22	0.53
Hypertension	-0.02	0.12	0.88	-0.25	0.22
	Mental health				
Depression	0.21	0.18	0.23	-0.13	0.56
Stress	0.04	0.16	0.81	-0.28	0.36
	Personality				
Openness	0.00	0.00	0.64	0.00	0.01
Neuroticism	0.00	0.00	0.33	-0.01	0.00
Conscientiousness	0.00	0.00	0.90	0.00	0.00
Agreeableness	0.00	0.00	0.87	0.00	0.00
Extroversion	0.00	0.00	0.12	-0.01	0.00

Appendix 16: Table (F) Significant weight loss of individuals engaged at week 12
Maximum Likelihood Estimation including the Inverse Mills Ratio as a regressor (n=851)

Variable	Coef.	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Constant	-1.61	1.37	0.24	-4.30	1.07
Inverse Mills Ratio (λ)	0.31	0.70	0.65	-1.06	1.68
	Demographics				
Male	-0.03	0.19	0.88	-0.40	0.34
Age	0.05	0.03	0.10	-0.01	0.10
Age squared	0.00	0.00	0.21	0.00	0.00
White (ethnicity)	0.89	0.56	0.11	-0.20	1.98
Indices of deprivation	-0.02	0.02	0.46	-0.06	0.03
Partner	0.08	0.11	0.47	-0.14	0.31
Presence of Children	-0.42	0.20	0.04	-0.80	-0.03
Employed	-0.12	0.13	0.36	-0.37	0.13
Degree level education	0.25	0.16	0.11	-0.06	0.57
Perception of local area	0.00	0.00	0.94	-0.01	0.01
	Weight factors				
BMI (initial)	-0.03	0.02	0.05	-0.07	0.00
Weight change (kg) week 2	-0.30	0.10	0.00	-0.51	-0.10
	Aspect of the programme				
Self-referred	0.06	0.10	0.57	-0.14	0.26
Days (referral to registration)	0.00	0.00	0.58	-0.01	0.01
Days (registration to start)	0.02	0.01	0.03	0.00	0.04
Consistent attendance	0.88	0.31	0.00	0.28	1.49
	Health behaviours				
Smokes	0.18	0.20	0.38	-0.22	0.57
Excess alcohol consumption	-0.23	0.20	0.26	-0.62	0.17
Perception of diet	0.00	0.00	0.87	-0.01	0.01
Energy expenditure (kcal/day)	0.00	0.00	0.25	0.00	0.00
	Physical health				
Disabled	0.12	0.26	0.64	-0.38	0.63
Cardiovascular disease	0.00	0.19	0.99	-0.37	0.37
Mobility problems	0.13	0.13	0.32	-0.13	0.38
Diabetes	-0.50	0.23	0.03	-0.95	-0.04
Hypertension	0.16	0.14	0.26	-0.12	0.44
	Mental health				
Depression	0.09	0.19	0.64	-0.28	0.46
Stress	-0.39	0.25	0.12	-0.87	0.10
	Personality				
Openness	0.00	0.00	0.43	-0.01	0.00
Neuroticism	0.00	0.00	0.69	0.00	0.01
Conscientiousness	0.00	0.00	0.39	-0.01	0.00
Agreeableness	0.00	0.00	0.97	-0.01	0.01
Extroversion	0.00	0.00	0.43	0.00	0.01

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